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Introduction to IoT, AI, and ML in Sustainable Communication

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1.1 Introduction

In the contemporary digital era, the convergence of the Internet of Things (IoT), artificial intelligence (AI), and machine learning (ML) has emerged as a pivotal force reshaping communication infrastructures, decision-making paradigms, and sustainable development strategies across critical sectors. These technologies are not only advancing technical capacities but also addressing complex global challenges – ranging from climate change and resource scarcity to healthcare delivery and urban management [1, 2].

IoT technologies provide the foundational infrastructure for real-time data acquisition through a distributed network of sensors and actuators. This continuous stream of data becomes valuable when integrated with AI systems capable of extracting actionable insights via advanced computational techniques, while ML models refine and enhance predictive capabilities through iterative learning from historical and dynamic datasets [3, 4]. The synergy between these technologies plays a central role in enhancing operational efficiency, reducing waste, and promoting sustainability across domains such as agriculture, smart cities, and healthcare [5–8].

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In agriculture, for example, IoT-enabled sensors facilitate precise monitoring of environmental variables such as soil moisture, crop health, and weather patterns. These data streams are analyzed by AI systems to optimize irrigation, fertilization, and pest control practices. Simultaneously, ML models enable predictive analytics for yield estimation, disease forecasting, and adaptive decision support [9, 10]. In urban environments, smart cities leverage IoT technologies to manage infrastructure systems, such as traffic, energy consumption, waste collection, and environmental monitoring, through real-time sensing and control mechanisms [11]. AI algorithms enable real-time analysis of traffic congestion and environmental data to optimize public service delivery, while ML facilitates long-term planning by modeling patterns of population growth, energy demand, and mobility behaviors [12, 13]. In healthcare, wearable IoT devices enable continuous monitoring of physiological parameters, generating data that support early disease detection and remote patient management. AI-based diagnostic tools assist clinicians in interpreting complex datasets, while ML techniques enhance the personalization of treatment plans and predict disease progression trends [14–16].

Despite their transformative potential, the deployment of IoT–AI–ML ecosystems poses considerable challenges. Key issues include the management and integration of large-scale heterogeneous data, ensuring privacy and cybersecurity across interconnected systems, and mitigating the environmental impact of energy-intensive computational processes [17, 18]. To address these barriers, emerging solutions such as edge computing, federated learning (FL) [19], and energy-efficient AI-specific hardware [20] are being increasingly adopted. Thus, the chapter aims to offer a comprehensive examination of the foundational principles, interdependencies, and emerging applications of IoT, AI, and ML in the context of sustainable communication systems. By drawing upon recent academic and industrial advancements [21–23], we highlight the transformative impact of these technologies and discuss their role in enabling scalable, intelligent, and ethically responsible infrastructures that align with global sustainability imperatives.

1.2 Foundational Principles of IoT, AI, and ML

1.2.1 IoT as the Backbone of Intelligent Communication Systems

The IoT signifies a transformative technological paradigm, enabling physical objects – ranging from basic sensors to advanced embedded systems – to connect, interact, and exchange data across network infrastructures in real time. This networked environment empowers systems to make autonomous decisions, adapt to environmental changes, and offer predictive capabilities in diverse domains including agriculture, healthcare, smart cities, logistics, and manufacturing [24, 25].

1.2.1.1 Architectural Overview

IoT systems are typically structured into a three-layer architecture, which underpins the end-to-end flow of data and functionality:

- **Perception Layer**: This foundational layer consists of sensors and actuators that interact directly with the physical environment. These components are responsible for detecting variables such as temperature, pressure, humidity, motion, and biochemical changes [26]. For example, in smart farming, sensors are used to monitor soil moisture and nutrient levels, providing the groundwork for intelligent decision-making [24].
- **Network Layer**: The intermediary layer is responsible for transferring the data acquired at the perception layer to cloud platforms or edge systems. It employs a variety of communication protocols, including Wi-Fi [27], Bluetooth [28], ZigBee [29], and LoRaWAN [30], to ensure reliable data transmission. Recent studies also explore the integration of blockchain and secure protocols to ensure lightweight authentication and confidentiality in medical and industrial IoT applications [31, 32].
- **Application Layer**: At the top of the hierarchy, this layer processes the transmitted data, transforming it into actionable insights for various verticals such as healthcare diagnostics, industrial automation, or intelligent transportation systems [26, 33]. ML models and AI-based inference engines are commonly implemented at this level to drive intelligent decision-making [34].

Figure 1.1 visually captures this tri-layer framework and the seamless interplay of IoT components across it. This structure is essential for enabling scalability, interoperability, and system resilience in complex environments.

The perception layer consists of physical sensors and devices responsible for data collection. The network layer transmits the collected data using communication technologies such as 4G/LTE, ZigBee, Z-Wave, Bluetooth, and Wi-Fi. The application layer processes and utilizes the data for intelligent decision-making in domains such as cloud computing, smart transportation, smart environments, and smart homes.

1.2.1.2 Foundational Capabilities and Communication Technologies

Modern IoT applications demand high scalability and energy efficiency, necessitating the development of lightweight architectures and adaptive routing protocols [35]. Innovative approaches such as multimedia sensing as a service (MSaaS) and cognitive-LPWANs are being introduced to support real-time analytics at the edge while reducing network congestion [36]. Similarly, concepts like Hybrid Energy Harvesting Things (HEHT) propose self-sustainable IoT deployments that leverage renewable energy sources [37].

Security and privacy remain major concerns in IoT ecosystems. Numerous frameworks have been proposed to safeguard data integrity and user anonymity, including Stackelberg game-based physical layer security enhancements [38] and

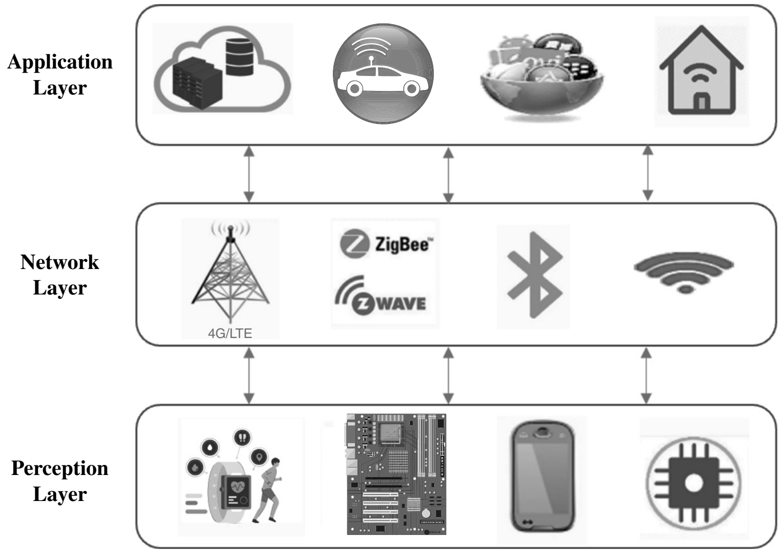

Figure 1.1 Three-layer architecture of the Internet of Things (IoT).

secret key generation mechanisms using turbo codes for vehicular networks [39]. With the proliferation of ultra-dense sensor networks, the integration of semantic communication and intelligent network slicing has also become essential [40].

1.2.1.3 Scalability, Positioning, and Real-time Processing

From a foundational perspective, IoT systems are defined by their ability to ensure interoperability, scalability, low latency, and energy efficiency. Scalability is achieved through modular device deployment, which allows seamless integration of new devices into the network [41]. Interoperability, on the other hand, is addressed through standardization protocols and middleware frameworks that enable devices from different manufacturers to work together [42]. Furthermore, the evolution of IoT has been accelerated by the integration of cloud and edge computing, allowing more efficient and distributed processing of data close to the source. Edge computing particularly enhances the performance of time-sensitive applications by reducing latency and minimizing bandwidth requirements [43].

Recent innovations in IoT have emphasized scalable scheduling mechanisms like PID-based control for 6TiSCH networks [44] and the simulation of interference patterns in LPWANs for optimized network planning [45]. Meanwhile, efforts in PNT (positioning, navigation, and timing) using LEO satellites demonstrate the feasibility of enhancing IoT localization accuracy and temporal synchronization at scale [46]. These developments not only optimize operational efficiency but also address critical concerns regarding data privacy, security, and energy consumption [47].

1.2.2 AI: Foundations, Evolution, and Role in Sustainable Communication

AI is broadly defined as the ability of machines to mimic cognitive functions such as learning, reasoning, and problem-solving, traditionally associated with human intelligence [48]. Over the past few decades, the rapid development of computational power, availability of big data, and advances in ML have collectively propelled AI into virtually every industry. In the context of sustainable communication systems, AI acts as a transformative enabler that supports intelligent decision-making, automation, and predictive analytics across domains such as energy, healthcare, agriculture, and urban planning [49–54].

AI's current landscape reflects a shift from rule-based systems to data-driven paradigms, driven predominantly by ML, deep learning (DL), and natural language processing (NLP). These techniques allow systems to adapt and learn from real-time data, rendering them highly valuable in dynamically changing environments [55]. For example, NLP has become instrumental in automating clinical documentation and extracting actionable insights from unstructured healthcare records [56–59]. In sustainable communication systems, AI is integrated with the IoT to analyze sensor-generated data, identify inefficiencies, and optimize performance without human intervention. This synergy allows for real-time monitoring of environmental variables, infrastructure, and human activity, supporting resource conservation and operational efficiency [60].

Furthermore, AI contributes to energy sustainability by enhancing energy management systems through predictive analytics, enabling demand forecasting, fault detection, and energy-efficient control strategies [60, 61]. In agriculture, AI-driven algorithms are increasingly used to model crop growth patterns, optimize irrigation scheduling, and detect plant diseases from satellite images or drone footage [62]. From an industrial and societal perspective, AI has also made significant strides in improving decision-making in complex environments. For instance, the application of AI in financial forecasting, supply chain optimization, and smart manufacturing demonstrates its role in streamlining processes and reducing wastage [63, 64].

However, alongside these advancements, AI introduces challenges related to interpretability, data privacy, and ethical deployment. There is an increasing call for responsible AI frameworks that promote transparency, fairness, and accountability in automated decision systems, particularly in sensitive applications such as healthcare and human resources [65, 66]. To contextualize the diversity of AI techniques and their applicability across domains, Table 1.1 presents a comparison of widely used AI methods, their foundational concepts, and their relevance to sustainable communication environments.

Table 1.1 Foundational AI techniques and their relevance in sustainable communication.

AI technique	Primary function	Application domain	Strengths	Limitation
Supervised learning	Predict outcomes from labeled data	Energy forecasting, diagnostics	High accuracy, robust prediction	Requires labeled data
Unsupervised learning	Discover patterns in unlabeled data	Customer segmentation, clustering	Insightful for hidden trends	Difficult to validate results
Reinforcement learning	Learn through trial and error interactions	Autonomous systems, robotics	Adaptive, suited for dynamic environments	Slow convergence, exploration risks
Deep learning	Layered neural networks for complex patterns	Image recognition, natural language processing (NLP)	High accuracy, complex feature learning	Opaque, resource-intensive
NLP	Understand and generate human language	Clinical records, chatbot systems	Automates unstructured data analysis	Context understanding remains limited

Note: The content of this table is synthesized from key insights and findings reported in the current literature.

1.2.3 ML: Core Enabler of Intelligent and Sustainable Communication Systems

ML has become a cornerstone of intelligent system design in the era of data-centric innovation. As sustainable communication systems increasingly depend on data analytics, real-time decision-making, and autonomous operations, ML offers powerful tools to process complex data, adapt to dynamic environments, and continuously improve system efficiency. Within the realm of IoT and AI, ML acts as the adaptive layer that enhances system performance, reduces energy usage, and facilitates robust predictive capabilities – thereby supporting the Sustainable Development Goals (SDGs) through smarter technology deployment.

ML encompasses a variety of algorithmic approaches such as supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, and DL. These techniques are deployed to extract actionable insights from vast datasets in real time, improving applications in domains like edge computing, healthcare diagnostics, environmental monitoring, smart cities, agriculture, and network optimization. Among these, reinforcement learning and FL are gaining momentum due to their ability to personalize learning models at the edge while ensuring data privacy and energy efficiency. For instance, Zhang et al. (2024) proposed deep reinforcement learning (DRL)-enhanced methods for energy-efficient IoT systems, while Lu et al. [67] systematically reviewed the role of ML in intelligent IoT service composition. Ghafari and Mansouri [68] further explored resource optimization through RL in fog computing, addressing scalability and latency in distributed networks.

Furthermore, TinyML, a branch of ML for resource-constrained environments, is being integrated into edge devices, facilitating decentralized learning with minimal energy consumption. Applications include indoor air quality monitoring, smart agriculture, traffic light control, and emotion recognition through physiological signals. These innovations are not only reshaping the technical landscape but also redefining how sustainable, autonomous systems are built and deployed. Table 1.2 highlights prominent applications and trends in ML technologies used in sustainable communication and IoT systems.

Table 1.2 Key ML trends and applications in sustainable communication systems.

ML approach	Application domain	Objective/contribution	Reference(s)
Deep reinforcement learning	Edge computing for IoT	Latency and resource optimization	[69]
Supervised learning	Smart IoT security	Classification of threats and intrusion detection	[70]
Unsupervised learning	Environmental sensor anomaly detection	Real-time fault recognition	[71]
Deep learning	Emotion recognition and medical imaging	Image analysis and diagnosis	[72]
Hybrid learning	Traffic management systems	Dynamic traffic signal control	[73]
TinyML	Audio and keyword spotting	Low-power intelligent processing	[74]
Semi-supervised learning	Smart cities and edge devices	Resource-aware decision-making	[75]
GANs (Generative)	Predictive healthcare and security systems	Enhanced realism and model generalizability	[76, 77]
Reinforcement learning	Routing and task offloading in IoT	Energy-efficient and adaptive scheduling	[76, 78]

Note: This table has been constructed based on a critical synthesis of insights from peer-reviewed literature in the ML and IoT domains.

1.3 Synergistic Integration of IoT, AI, and ML for Sustainable Communication Systems

The convergence of the IoT, AI, and ML represents a pivotal transformation in the design and implementation of sustainable communication systems. Each technology individually contributes to the digitization and automation of processes; however, their integration amplifies the impact, offering scalable, intelligent, and sustainable solutions for global challenges in healthcare, agriculture, infrastructure, smart cities, and industrial sectors [79–83]. This triad enables systems that are not only connected and data-rich but also capable of adaptive, predictive, and autonomous decision-making.

1.3.1 Enabling Architecture and Interoperability

The successful integration of the IoT, AI, and ML into sustainable communication systems hinges on a robust architectural framework and seamless interoperability across diverse components. This interoperability is essential not only for real-time data exchange but also for enabling intelligent decision-making processes that adapt dynamically to changing environmental, infrastructural, and user demands.

1.3.1.1 Middleware and Semantic Interoperability

A key challenge in enabling this multilayered ecosystem is ensuring interoperability, the ability of heterogeneous devices, platforms, and services to communicate and function cohesively. This requires:

- ***Middleware Platforms***: These act as a bridge between hardware and software layers, managing tasks like data formatting, message brokering, security, and device orchestration. Examples include open-source platforms such as FIWARE or proprietary solutions like AWS IoT Core and Google Cloud IoT.
- ***Semantic Interoperability***: Beyond syntax-level compatibility, systems must also understand the meaning of the data exchanged. This is where ontologies and standardized data models (e.g. W3C's Semantic Sensor Network ontology) are used to facilitate meaningful interactions between AI/ML models and IoT systems [81].

1.3.1.2 Distributed Versus Centralized Intelligence

Traditional IoT architectures rely on centralized cloud-based analytics, where vast amounts of data are transmitted to the cloud for processing. However, such models face limitations related to latency, bandwidth, and data privacy. To address these, Edge Computing and Fog Computing architectures are increasingly being adopted:

- *Edge artificial intelligence (Edge AI)* allows AI/ML algorithms to be deployed directly on local devices (e.g. sensors, smartphones, microcontrollers), enabling on-device intelligence with minimal latency and reduced cloud dependency [84, 85].
- *Fog computing* bridges the gap between the cloud and the edge by providing intermediate processing nodes that offer faster response and enhanced scalability.

These distributed paradigms not only improve responsiveness but also reduce energy consumption and support green computing goals, particularly when deployed with efficient ML models such as FL [86].

1.3.1.3 Interoperability Standards and Protocols

Achieving system-wide compatibility requires adherence to standardized communication protocols, data formats, and security frameworks. Commonly used standards include:

- **MQTT and CoAP**: Lightweight messaging protocols suited for constrained devices and networks.
- **JSON, XML**: Common data serialization formats.
- **IEEE 802.15.4/ZigBee/BLE**: Communication standards for low-power wireless personal area networks.

Security and privacy standards such as HIPAA (in healthcare) or General Data Protection Regulation (GDPR) (in Europe) also govern the processing and exchange of sensitive data, especially when AI/ML systems operate on personal information [47, 87–89].

1.3.1.4 Role of Digital Twins and System-level Integration

One emerging trend in integrated architecture is the deployment of digital twins-virtual representations of physical systems. These twins are updated in real time via IoT sensors, allowing AI models to simulate, test, and optimize performance under different scenarios [90]. This is particularly relevant in smart infrastructure, where system-level integration of AI and IoT enhances predictive maintenance, resource allocation, and emergency response planning.

Thus, the integration of IoT, AI, and ML requires a multilayered architectural approach that spans perception, network, and application layers. At the perception layer, IoT devices collect environmental and operational data. The network layer transmits this data to centralized or decentralized platforms using protocols such

Table 1.3 Functional synergies of IoT, AI, and ML across domains.

Domain	Role of IoT	Role of AI	Role of ML
Healthcare	Real-time health monitoring via wearables	Anomaly detection and diagnostic support	Predictive analytics for personalized treatment
Smart cities	Traffic sensors, waste and energy monitoring	Urban planning, dynamic resource allocation Classification of threats and intrusion detection	Demand forecasting, route optimization
Agriculture	Soil and crop sensing	Yield optimization, disease identification	Pattern detection in weather/crop data
Industry 4.0	Equipment and environmental monitoring	Predictive maintenance	Quality control and anomaly detection
Tourism	Visitor movement tracking	Recommendation systems	Customer behavior prediction

Note: This table has been constructed based on a critical synthesis of insights from peer-reviewed literature in the AI, ML, and IoT application domains.

as 5G, ZigBee, or LoRaWAN [91, 92]. AI and ML are embedded in the application layer, where data is processed, analyzed, and interpreted for actionable insights in real time [85]. This architectural interplay enhances the operational intelligence of various systems. For example, in smart agriculture, IoT sensors monitor soil and climate conditions, AI models optimize irrigation schedules, and ML algorithms predict pest outbreaks and crop health [93, 94]. As shown in Table 1.3, the integration of IoT, AI, and ML offers complementary functionalities across multiple sectors, enabling data-driven optimization and real-time responsiveness.

1.3.2 Applications in Key Domains

The integration of IoT, AI, and ML has given rise to intelligent, responsive, and sustainable solutions across various sectors, as outlined in Table 1.4. This synergy not only enhances real-time monitoring and automation but also strengthens system intelligence and adaptability. Below are key domain-specific use cases demonstrating this integration.

1.3.2.1 Healthcare and Internet of Medical Things

The convergence of IoT, AI, and ML in healthcare has laid the foundation for what is now known as the Internet of Medical Things (IoMT). Wearable IoT devices, such as smartwatches, implantable sensors, and portable ECG monitors,

Table 1.4 Comparative strengths of IoT, AI, and ML in sustainable communication systems.

Technology	Core of strengths	Limitations	Potential enhancements via integration
IoT	Real-time data acquisition, device interconnectivity, environmental sensing	Vulnerable to data overload, cybersecurity threats, energy constraints	AI for data filtering and anomaly detection; ML for pattern learning and event prediction
AI	Decision-making, real-time optimization, autonomous system control	High computational demands, data dependency, explainability issues	IoT for real-time contextual inputs; ML for continuous model refinement
ML	Pattern recognition, predictive analytics, anomaly detection	Requires large training datasets, prone to bias, lacks transparency	IoT for diverse data input; AI for intelligent decision-making and interpretability

Note: This table has been developed based on synthesized insights from domain-specific literature across healthcare, urban infrastructure, and agriculture [42, 97, 99–101].

enable continuous collection of vital health data. AI algorithms analyze these data streams to detect abnormalities, flag health risks, and recommend interventions in real time. For instance, AI-powered triage tools use symptom data from mobile apps to prioritize patients during telemedicine consultations.

ML further personalizes this process by identifying disease patterns, predicting hospital readmissions, and supporting clinical decision-making based on longitudinal health records. In chronic disease management, ML models now forecast glucose trends in diabetic patients or predict cardiac arrhythmias based on ECG patterns. Privacy-preserving techniques like FL are becoming essential in healthcare, allowing for decentralized training of ML models across devices while protecting sensitive patient data [95–97]. Moreover, AI-powered robotic process automation is revolutionizing administrative workflows, improving patient throughput, and reducing human error in hospital systems.

1.3.2.2 Sustainable Urban Infrastructure

Smart cities are at the forefront of deploying IoT, AI, and ML to improve urban sustainability and resilience. IoT devices embedded in traffic signals, vehicles, streetlights, and environmental stations enable the real-time collection of data on mobility, air quality, noise levels, and energy consumption. AI dynamically optimizes traffic flow by adjusting signals in response to real-time congestion patterns, reducing idle time and emissions [42].

ML algorithms enhance long-term urban planning by analyzing historical data on public transport usage, pedestrian flows, and accident patterns. These insights inform city planners on infrastructure investments, route adjustments, and emergency preparedness. In waste management, smart bins with IoT sensors alert collection services when full, while AI routes optimize collection and disposal paths, improving efficiency and reducing fuel consumption [81]. Additionally, environmental monitoring systems powered by AI/ML predict pollution surges and guide interventions, such as rerouting traffic or issuing public health alerts. These integrated solutions collectively support data-centric governance for sustainable urban ecosystems.

1.3.2.3 Precision Agriculture and Food Security

In agriculture, the synergy of IoT, AI, and ML underpins precision farming, a transformative approach to maximizing productivity while conserving resources. IoT sensors embedded in fields and on farm equipment gather real-time data on soil moisture, nutrient levels, temperature, and crop health. Drones equipped with IoT modules capture aerial imagery, enabling high-resolution monitoring of crop growth and pest infestations.

AI-driven analytics then evaluate the collected data to recommend optimized irrigation schedules, fertilizer application, and pest control measures. For example, AI can classify crop diseases from leaf images and suggest treatment strategies, minimizing pesticide use. ML models predict yield variations based on weather forecasts, soil profiles, and historical crop data, enabling farmers to make informed planting and harvesting decisions [98, 99]. Furthermore, the use of AI-based robotics in autonomous tractors and harvesters enhances operational efficiency and reduces labor dependency, which is particularly valuable during labor shortages or pandemics. These integrated systems contribute to sustainable food production and bolster food security, especially in regions vulnerable to climate variability.

1.4 Challenges in Implementation

The convergence of IoT, AI, and ML has introduced unprecedented possibilities in advancing sustainable communication systems. However, despite their synergistic potential, the integration and practical implementation of these technologies remain fraught with significant challenges. These obstacles span technical, ethical, legal, and infrastructural dimensions, making their resolution critical for widespread adoption. Furthermore, as summarized in Table 1.5, each technological pillar brings unique strengths and limitations to the integrated system, and

Table 1.5 Key challenges in implementing integrated IoT–AI–ML systems.

Challenge category	Description	Potential mitigation strategies
Data security and privacy	Vulnerability to cyber threats and data breaches	Federated learning, encryption, blockchain
Scalability and interoperability	Lack of standardization, fragmented ecosystems	Open standards, middleware, cross-platform APIs Classification of threats and intrusion detection
Resource constraints	Limited energy, bandwidth, and processing power in edge devices	Requires large training datasets, prone to bias, lacks transparency Energy-efficient hardware, Edge AI, optimized ML models
Ethical and regulatory	Bias in AI, lack of transparency, unclear data governance	Explainable AI, updated data policies, ethics frameworks
Real-time processing	Delays due to centralized computation and network bottlenecks	Edge computing, lightweight AI/ML algorithms
Skills gap	Shortage of qualified professionals across disciplines	Capacity building programs, cross-sector collaboration

Note: This table has been developed based on a synthesis of insights derived from the current literature and expert discussions on implementation bottlenecks across integrated IoT, AI, and ML systems.

understanding these distinctions is essential for effective deployment and optimization in real-world scenarios.

1.4.1 Data Security and Privacy Concerns

A primary concern in the deployment of IoT, AI, and ML systems is data security and privacy. With massive volumes of sensitive data transmitted across networks, systems are vulnerable to cyber threats such as denial-of-service (DoS) attacks, eavesdropping, and data breaches [102–105]. The distributed and heterogeneous nature of IoT devices often leads to inconsistent security protocols, making it difficult to ensure end-to-end data protection [106]. Furthermore, AI-driven analytics can inadvertently expose private user information if models are not adequately anonymized [107]. FL and homomorphic encryption are emerging as privacy-preserving solutions, but they require high computational resources and reliable communication infrastructure, which are often lacking in low-power IoT environments [108, 109].

1.4.2 Scalability and Interoperability

As smart infrastructures grow, ensuring scalability and interoperability becomes essential yet complex. Diverse device manufacturers, proprietary communication protocols, and nonuniform data formats hinder seamless integration [110, 111]. AI models may need to be retrained or adapted for each platform, complicating deployment. Interoperability challenges are especially pronounced in urban infrastructure and healthcare applications where real-time coordination across multiple systems is mandatory [112, 113]. Standardization efforts such as IEEE 1451 for sensor networks and edge computing frameworks provide partial solutions, but widespread adoption remains slow.

1.4.3 Resource Constraints and Infrastructure Gaps

IoT devices are often deployed in environments with limited power, bandwidth, and computational capacity. ML algorithms, particularly DL models, are resource-intensive, requiring robust hardware and software ecosystems [114, 115]. Many developing regions lack the infrastructure to support real-time analytics or secure cloud services, leading to implementation disparities [116, 117]. Furthermore, sustainable communication systems require energy-efficient solutions, yet many IoT deployments contribute to increased carbon footprints due to inefficient architectures or overprovisioned networks [118].

1.4.4 Ethical and Regulatory Issues

The ethical implications of AI decision-making, especially in critical domains such as healthcare and law enforcement, pose substantial challenges. AI models may inherit biases from training data, resulting in unfair or discriminatory outcomes [119]. Additionally, the lack of clear regulatory guidelines for data ownership, accountability, and transparency limits stakeholder trust and hinders large-scale adoption [120]. Frameworks like the EU's GDPR and initiatives for explainable AI (XAI) offer guidance, but more sector-specific regulations are needed for operational clarity [88].

1.4.5 Real-time Processing and Latency

The need for real-time decision-making in critical applications, such as autonomous vehicles, healthcare monitoring, and industrial control systems, demands ultra-low latency and high-speed data processing. Traditional cloud architectures are not sufficient to meet these requirements, and although edge computing presents a solution, its integration with AI/ML is still maturing [121, 122]. Edge devices must be capable of hosting lightweight AI models, managing intermittent connectivity, and coordinating with cloud servers – all of which increase the complexity of deployment.

1.4.6 Human Capital and Skills Gap

Finally, the successful implementation of IoT–AI–ML systems requires a multidisciplinary workforce with expertise in data science, embedded systems, networking, and cybersecurity. However, there exists a significant talent gap, particularly in low-resource settings, limiting the potential for widespread adoption and innovation [103, 107].

1.5 Emerging Trends and Future Perspectives

1.5.1 Edge AI and FL

A key trend in the AI and IoT convergence is the migration of computational intelligence from centralized cloud architectures to the edge. Edge AI enables real-time analytics directly on devices, reducing latency, improving responsiveness, and addressing data privacy concerns [123, 124]. Recent frameworks such as ToEFL [125] and privacy-preserving SVMs [126] demonstrate how edge models can be efficiently trained and deployed with minimal resource consumption. FL, as emphasized in multiple studies [127, 128], complements Edge AI by allowing distributed devices to collaboratively learn global models without exchanging raw data. This preserves privacy while ensuring scalability, making it ideal for sectors like healthcare, finance, and smart cities. Additionally, recent efforts have investigated lightweight FL architectures that can be integrated into resource-constrained IoT systems [129, 130].

1.5.2 Energy-efficient and Green AI

The sustainability implications of massive data processing have led to the rise of energy-efficient AI techniques. Green AI refers to practices that minimize the carbon footprint of model training and inference by optimizing resource usage [131, 132]. This includes hardware-aware model pruning, quantization, and the deployment of TinyML models for edge inference [133]. Moreover, research in lightweight ML deployment has gained traction, with innovations focusing on reducing memory and power consumption while maintaining predictive accuracy [134, 135]. These methods support sustainable applications such as predictive maintenance, precision agriculture, and disaster risk reduction in remote areas.

1.5.3 Integration with Industry 4.0 and Cyber-physical Systems

The transition to Industry 4.0 is inherently dependent on the seamless interaction between digital technologies and physical systems. AI- and IoT-driven cyber-physical systems are now enabling real-time synchronization between digital twins and their physical counterparts, allowing predictive simulations, quality control, and adaptive manufacturing [131, 134]. As highlighted by Anukiruthika and Jayas [137], AI-based automation in agriculture and grain storage can significantly reduce postharvest losses and ensure food security. Similarly, smart logistics using edge-enabled IoT platforms are improving efficiency in transportation and supply chains [138].

1.5.4 Security and Privacy in Intelligent Systems

Security remains a persistent challenge in IoT–AI integration. With devices becoming smarter and more autonomous, vulnerabilities across the network stack require robust solutions. Recent studies have proposed federated intrusion detection systems and blockchain-enhanced IoT platforms as potential defenses [128, 139]. The future of secure AI includes context-aware access control, self-healing systems, and anomaly detection models that operate continuously at the edge. Additionally, privacy-aware data collection methods and GDPR-compliant processing workflows are becoming standard in smart applications [123, 140].

1.5.5 Hybrid and Multimodal Models for Smart Decision-making

An emerging direction in AI research involves hybrid architectures combining symbolic reasoning with DL and multimodal inputs (vision, speech, sensor data). These enable context-aware, human-centric systems with improved explainability [124, 125]. In particular, healthcare, disaster management, and elder care systems benefit from such enriched data-processing capabilities. Table 1.6 summarizes emerging technological directions and their practical applications across various domains.

1.5.6 Future Outlook

Looking forward, the continued evolution of the IoT, AI, and ML ecosystem could be governed by a combination of technological advancements, socio-ethical frameworks, and interdisciplinary collaboration. Among the most transformative trends shaping this trajectory is the rise of XAI, which seeks to demystify the internal workings of complex models and foster trust among stakeholders by offering transparent, interpretable insights [142]. As AI systems increasingly

Table 1.6 Overview of emerging trends in IoT–AI–ML integration and application domains.

Trend	**Description**	**Domains of impact**	**Reference(s)**
Edge AI	On-device inference with reduced latency and privacy risk	Healthcare, transportation, agriculture	[124, 125, 141]
Federated learning	Collaborative learning without centralized data	Finance, smart cities, IoMT	[127, 128]
Tiny ML & green AI	Resource-efficient ML for sustainability	IoT devices, environmental monitoring	[133, 135]
Cyber–physical systems	Real-time coordination between digital and physical components	Industry 4.0, smart grids, warehousing	[131, 134]
AI for food security	Optimized postharvest management and yield prediction	Agriculture, supply chains	[135]
AI-enabled smart logistics	Efficient goods movement with adaptive routing	Transport, logistics, E-commerce	[136]
Blockchain and secure IoT	Ensuring integrity and traceability of data across decentralized networks	Finance, healthcare, industrial IoT	[137]
Hybrid AI systems	Combining symbolic logic with deep neural networks	Emergency response, personalized healthcare	[125, 140]

Note: Table compiled based on synthesized findings from recent literature and technological forecasts.

permeate high-stakes domains, such as healthcare diagnostics, autonomous transportation, and energy management, there is a growing demand for models that not only perform accurately but can also justify their decisions in a manner understandable to humans [123, 125].

In parallel, the emergence of responsible AI frameworks emphasizes the importance of aligning technological development with ethical values, fairness, privacy, and human-centric design principles. This includes mitigating algorithmic biases, ensuring data sovereignty, upholding cybersecurity, and implementing socially accountable governance structures. Regulations such as the EU AI Act and the GDPR exemplify the growing institutional effort to establish legal guardrails around the use of AI and IoT systems. These developments will significantly shape how systems are designed, trained, and deployed in both public and private sectors [88].

Simultaneously, quantum ML (QML) is gaining momentum as an emergent frontier that promises exponential improvements in processing speed and problem-solving complexity. Although still in its infancy, QML could revolutionize data analytics in domains with vast multidimensional datasets, such as climate modeling, genomics, and smart energy systems. As researchers develop hybrid quantum-classical algorithms, the integration of quantum computing with edge and cloud infrastructure is expected to accelerate next-generation decision-making frameworks [133, 140].

Furthermore, interoperability and standardization play a critical role in ensuring seamless integration across platforms and sectors. Without unified data formats, communication protocols, and security policies, the synergistic potential of IoT, AI, and ML cannot be fully realized. Industry alliances, such as the Industrial Internet Consortium (IIC), and initiatives by international standard-setting bodies (e.g. IEEE, ISO) are already contributing to this endeavor. These efforts are crucial for facilitating the scalability and reliability of smart infrastructure across borders and applications. The convergence of academia, industry, and policy-making is also anticipated to become a dominant force in shaping sustainable innovation. Multi-stakeholder collaborations and public–private partnerships will be essential to translate foundational research into scalable, real-world solutions. Academic institutions are expected to play a key role in nurturing transdisciplinary expertise, while industry actors can provide technological infrastructure, and policymakers can establish ethical and legal frameworks to promote responsible innovation [89, 124, 131].

Additionally, the future landscape will likely be characterized by a strong push toward inclusivity and digital equity. Ensuring that AI and IoT technologies benefit all segments of society, including marginalized and underserved populations, will be critical in promoting global sustainability and resilience. This may involve the development of low-cost, localized AI solutions that are tailored to the unique needs of communities in low- and middle-income regions, thereby reducing the digital divide and fostering inclusive development. Technological foresight suggests we are entering an era where AI not only augments human decision-making but also evolves into a strategic enabler for achieving global sustainability objectives. From mitigating climate change to managing pandemics and optimizing food systems, AI-driven solutions, when responsibly implemented, can enhance our capacity to address multifaceted global challenges.

However, as these technologies become increasingly autonomous and self-adaptive, governance and foresight mechanisms must evolve in parallel.

This includes investing in anticipatory regulatory frameworks, dynamic risk assessment models, and participatory platforms that allow citizens to engage in shaping the digital future. Ultimately, a harmonized vision, rooted in human values, ecological responsibility, and technological innovation, will be central to shaping a future where IoT, AI, and ML act as stewards of sustainable progress.

1.6 Conclusion

The integration of the IoT, AI, and ML represents a transformative shift in how modern societies address sustainability, efficiency, and resilience in communication and infrastructure systems. The chapter provided a comprehensive overview of the foundational principles, architectural frameworks, application domains, and synergistic potential of these technologies, underscoring their collective ability to tackle complex global challenges, from healthcare to urban planning, environmental monitoring, and beyond. As demonstrated throughout the discussion, IoT functions as the sensory and data collection backbone, enabling real-time interactions with the physical environment. AI contributes intelligence by enabling systems to analyze, reason, and make decisions, while ML adds adaptability and prediction by learning from patterns within vast data streams. When synergized, these technologies facilitate highly responsive, context-aware, and efficient systems that are essential for sustainable development across critical sectors. However, the pathway toward full-scale deployment is not without obstacles. Challenges including data privacy, interoperability, energy consumption, ethical concerns, and regulatory alignment remain pressing and demand collaborative, multidisciplinary approaches. Addressing these hurdles requires robust governance frameworks, standardized communication protocols, transparent algorithms, and a human-centered design philosophy. Looking ahead, the future of sustainable communication will be increasingly defined by advancements in edge intelligence, FL, quantum computing, and XAI. These emerging technologies offer opportunities to enhance the security, scalability, and transparency of intelligent systems, ensuring that innovation aligns with societal and environmental needs. At the same time, fostering inclusive and equitable access to digital infrastructure will be critical to ensure that the benefits of these technologies are shared globally. In essence, the convergence of IoT, AI, and ML is not merely a technological trend, it is a foundational enabler of a smarter, greener, and more inclusive future. As researchers, engineers, policymakers, and practitioners continue to collaborate across boundaries, the vision of sustainable, intelligent communication systems can be realized in ways that truly serve both people and the planet.

References

1. Gubbi, J., Buyya, R., Marusic, S., and Palaniswami, M. (2013). Internet of Things (IoT): a vision, architectural elements, and future directions. *Future Generation Computer Systems* 29: 1645–1660.
2. Russell, S.J., and Norvig, P. (2016). *Artificial İntelligence: A Modern Approach*. Pearson.
3. Anik, S.M.H., Gao, X., Meng, N., et al. (2022). A cost-effective, scalable, and portable IoT data infrastructure for indoor environment sensing. *Journal of Building Engineering* 49: 104027.
4. Ramya, R. (2024). Analysis and applications finding of wireless sensors and IoT devices with artificial intelligence/machine learning. In: *AIoT and Smart Sensing Technologies for Smart Devices* (pp. 77–102). IGI Global Scientific Publishing.
5. Bodur, G., Turhan, Z., Kucukkaya, A., and Goktas, P. (2024). Assessing the virtual reality perspectives and self-directed learning skills of nursing students: a machine learning-enhanced approach. *Nurse Education in Practice* 75: 103881.
6. Ullah, A., Anwar, S.M., Li, J., et al. (2024). Smart cities: the role of Internet of Things and machine learning in realizing a data-centric smart environment. *Complex & Intelligent Systems* 10: 1607–1637.
7. Kupcu, C., Bodur, G., Kucukkaya, A., and Goktas, P. (2024). Assessing nursing students' e-health literacy and foresights to global health challenges during COVID-19 restrictions: a cross-sectional study with a machine learning approach. *Nurse Education in Practice* 81: 104179.
8. Kucukkuya, A., Bodur, G., Ozata, S.Y., and Goktas, P. (2025). Tapping into awareness: assessing nursing students' water consumption behaviors and sustainability perceptions through a cross-sectional study with machine learning approach. *Public Health Nursing* 42 (1): 444–456.
9. Khan, I.U., Ayub, M.Y., Abdollahi, A., and Dutta, A. (2023). A hybrid deep learning model-based intrusion detection system for emergency planning using IoT-network. *Proceedings of ICT-DM 2023*.
10. Zhang, M., Zhang, H., Yuan, D., and Zhang, M. (2019). Compressive sensing and autoencoder based compressed data aggregation for green IoT networks. In: *2019 IEEE Global Communications Conference (GLOBECOM)* (pp. 1–6). IEEE.
11. Badidi, E., Moumane, K., and Ghazi, F.E. (2023). Opportunities, applications, and challenges of edge-AI enabled video analytics in smart cities: a systematic review. *IEEE Access* 11: 80543.
12. Balasubramanian, S.B., Balaji, P., Munshi, A., et al. (2023). Machine learning based IoT system for secure traffic management and accident detection. *PeerJ Computer Science* 9: 1.

13 Jaiswal, S., Kumar Sharma, D., Jaiswal, T., et al. (2021). Real time analysis of intelligent placing system for vehicles using IoT with deep learning. *Materials Today: Proceedings* 51: 339.

14 Liang, F., Hatcher, W.G., Xu, G., et al. (2019). Towards online deep learning-based energy forecasting. In: *2019 28th International Conference on Computer Communication and Networks* (*ICCCN*) (pp. 1–9). IEEE.

15 Goktas, P., and Agildere, A.M. (2024). Transforming radiology with artificial intelligence visual chatbot: a balanced perspective. *Journal of the American College of Radiology* 21 (2): 224–225.

16 Goktas, P., and Damadoglu, E. (2024). Future of allergy and immunology: is AI the key in the digital era? *Annals of Allergy, Asthma & Immunology* 134 (4): 396–407.e2.

17 Sagduyu, Y.E., Shi, Y., and Erpek, T. (2019). IoT network security from the perspective of adversarial deep learning. In: *2019 16th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON*) (pp. 1–9). IEEE.

18 He, B., Wang, J., Qi, Q., et al. (2022). Intelligent provisioning of virtualized network functions in cloud of things: a deep reinforcement learning based approach. *IEEE Transactions on Cloud Computing* 10 (2): 1262.

19 Zhang, J., and Li, J. (2022). Mitigating bias and error in machine learning to protect sports data. *Computational Intelligence and Neuroscience* 2022 (1): 4777010.

20 Daghero, F., Pagliari, D.J., and Poncino, M. (2021). Energy-efficient deep learning inference on edge devices. In: *Advances in Computers* (Vol. 122, pp. 247–301). Elseiver.

21 Chen, Z., Tian, P., Liao, W., et al. (2023). Resource-aware knowledge distillation for federated learning. *IEEE Transactions on Emerging Topics in Computing* 11 (3): 706.

22 Liu, J., Wu, J., and Liu, M. (2020). UAV monitoring and forecasting model in intelligent traffic oriented applications. *Computer Communications* 153: 499.

23 Wu, Z., Huang, M., Zhao, A., and Lan, Z. (2021). Traffic prediction based on GCN-LSTM model. *Journal of Physics: Conference Series* 1972 (1): 012107.

24 Triantafyllou, A., Tsouros, D.C., Sarigiannidis, P., and Bibi, S. (2019). An architecture model for smart farming. *Proceedings – 15th Annual International Conference on Distributed Computing in Sensor Systems*. IEEE.

25 Chen, S., Ma, R., Chen, H.-H., et al. (2017). Machine-to-machine communications in ultra-dense networks—a survey. *IEEE Communications Surveys and Tutorials* 19 (3): 1478.

26 Goswami, P., Mukherjee, A., Hazra, R., et al. (2022). AI based energy efficient routing protocol for intelligent transportation system. *IEEE Transactions on Intelligent Transportation Systems* 23 (2): 1670.

27 Gast, M. (2006). *802.11 Wireless Networks: The Definitive Guide*. Southeast University Press.

28 Miller, B.A., and Bisdikian, C. (2001). *Bluetooth Revealed: The Insider's Guide to an Open Specification for Global Wireless Communications*. Prentice Hall.

29 Tennina, S., Koubâa, A., Daidone, R., et al. (2013). *IEEE 802.15.4 and ZigBee as Enabling Technologies for Low-Power Wireless Systems with Quality-of-Service Constraints*. Springer.

30 Jouhari, M., Amhoud, E.M., Saeed, N., and Alouini, M.S. (2022). A survey on scalable LoRaWAN for Massive IoT: recent advances, potentials, and challenges. *arXiv preprint arXiv:2202.11082*.

31 Wang, W., Chen, Q., Yin, Z., et al. (2022). Blockchain and PUF-based lightweight authentication protocol for wireless medical sensor networks. *IEEE Internet of Things Journal* 9 (11): 8883.

32 Du, H., Wang, J., Niyato, D., et al. (2023). Rethinking wireless communication security in semantic internet of things. *IEEE Wireless Communications* 30 (3): 36.

33 Patel, N.R., Kumar, S., and Singh, S.K. (2021). Energy and collision aware WSN routing protocol for sustainable and intelligent IoT applications. *IEEE Sensors Journal* 21 (22): 25282.

34 Aldossari, S.M., and Chen, K.-C. (2019). Machine learning for wireless communication channel modeling: an overview. *Wireless Personal Communications* 106 (1 Special Issue): 41.

35 Cakir, S., Toklu, S., and Yalcin, N. (2020). Rpl attack detection and prevention in the internet of things networks using a GRU based deep learning. *IEEE Access* 8: 183678.

36 Chen, M., Miao, Y., Jian, X., et al. (2019). Cognitive-LPWAN: towards intelligent wireless services in hybrid low power wide area networks. *IEEE Transactions on Green Communications and Networking* 3 (2): 409.

37 Akan, O.B., Cetinkaya, O., Koca, C., and Ozger, M. (2018). Internet of hybrid energy harvesting things. *IEEE Internet of Things Journal* 5 (2): 736.

38 Zhai, L., Zou, Y., Zhu, J., and Li, B. (2022). Improving physical layer security in IRS-aided WPCN multicast systems via Stackelberg game. *IEEE Transactions on Communications* 70 (3): 1957–1970.

39 Epiphaniou, G., Karadimas, P., Ben Ismail, D.K., et al. (2018). Nonreciprocity compensation combined with turbo codes for secret key generation in vehicular ad hoc social IoT networks. *IEEE Internet of Things Journal* 5 (4): 2496.

40 Lu, S., Liu, F., Li, Y., et al. (2024). Integrated sensing and communications: recent advances and ten open challenges. *IEEE Internet of Things Journal* 11 (11): 19094.

41 Sadeghi, A.R., Wachsmann, C., and Waidner, M. (2021). Security and privacy challenges in industrial internet of things. *Proceedings of the IEEE* 105 (1): 96–107.

42 Singh, R., and Rathore, H. (2021). A secure and scalable framework for IoT-based smart cities. *Procedia Computer Science* 185: 539–546.

43 Rahmani, A.M., Gia, T.N., Negash, B., et al. (2021). Exploiting smart e-health gateways at the edge of healthcare Internet-of-Things: a fog computing approach. *Future Generation Computer Systems* 78: 641–658.

44 Domingo-Prieto, M., Chang, T., Vilajosana, X., and Watteyne, T. (2016). Distributed PID-based scheduling for 6TiSCH networks. *IEEE Communications Letters* 20 (5): 1006.

45 Haxhibeqiri, J., Van den Abeele, F., Moerman, I., and Hoebeke, J. (2017). LoRa scalability: a simulation model based on interference measurements. *Sensors (Switzerland)* 17 (6): 1193.

46 Prol, F.S., Ferre, R.M., Saleem, Z., et al. (2022). Position, navigation, and timing (PNT) through low earth orbit (LEO) satellites: a survey on current status, challenges, and opportunities. *IEEE Access* 10: 83971.

47 Salman, T., Zolanvari, M., Erbad, A., et al. (2018). Security services using blockchains: a state of the art survey. *IEEE Communications Surveys & Tutorials* 21 (1): 858–880.

48 Ghahramani, Z. (2015). Probabilistic machine learning and artificial intelligence. *Nature* 521: 452–459.

49 Goktas, P., Rakholia, R., and Carbajo, R.S. (2023). Answering key questions about air pollution dynamics in Ho Chi Minh city: a spatiotemporal analysis using the XAI-SHAP clustering approach. In: *IFIP International Workshop on Artificial Intelligence for Knowledge Management* (pp. 189–203). Cham: Springer Nature Switzerland.

50 Goktas, P., Rakholia, R., and Carbajo, R.S. (2023). Investigating air pollution dynamics in Ho Chi Minh City: a spatiotemporal study leveraging XAI-SHAP clustering methodology. In: *European Conference on Artificial Intelligence* (pp. 201–207). Cham: Springer Nature Switzerland.

51 Goktas, P., Gulseren, D., and Tobin, A.M. (2024). Large language and vision assistant in dermatology: a game changer or just hype? *Clinical and Experimental Dermatology* 49 (8): 783–792.

52 Kucukkaya, A., Arikan, E., and Goktas, P. (2024). Unlocking ChatGPT's potential and challenges in intensive care nursing education and practice: a systematic review with narrative synthesis. *Nursing Outlook* 72 (6): 102287.

53 Goktas, P., and Dirsehan, T. (2025). Using PLS-SEM and XAI for causal-predictive services marketing research. *Journal of Services Marketing* 39 (1): 53–68.

54 Karaçay, P., Goktas, P., Yaşar, Ö., et al. (2025). Investigation of pressure injuries with visual ChatGPT integration: a descriptive cross-sectional study. *Journal of Advanced Nursing*. https://doi.org/10.1111/jan.16905.

55 L'Heureux, A., Grolinger, K., Elyamany, H.F., and Capretz, M.A.M. (2017). Machine learning with big data: challenges and approaches. *IEEE Access* 5: 7776–7797.

56 Demner-Fushman, D., Chapman, W.W., and McDonald, C.J. (2009). What can natural language processing do for clinical decision support? *Journal of Biomedical Informatics* 42 (5): 760–772.
57 Wang, Y., Wang, L., Rastegar-Mojarad, M., et al. (2018). Clinical information extraction applications: a literature review. *Journal of Biomedical Informatics* 77: 34–49.
58 Goktas, P., Kucukkaya, A., and Karacay, P. (2023). Leveraging the efficiency and transparency of artificial intelligence-driven visual Chatbot through smart prompt learning concept. *Skin Research and Technology* 29 (11): e13417.
59 Goktas, P., and Grzybowski, A. (2024). Assessing the impact of ChatGPT in dermatology: a comprehensive rapid review. *Journal of Clinical Medicine* 13 (19): 5909.
60 Ahmad, T., Zhang, D., Huang, C., et al. (2021). Artificial intelligence in sustainable energy systems: a review. *Journal of Cleaner Production* 289: 125449.
61 Li, L., Rong, S., Wang, R., and Yu, S. (2021). Recent advances in artificial intelligence and IoT. *Chemical Engineering Journal* 414: 128802.
62 Mamoshina, P., Ojomoko, L., Yanovich, Y., et al. (2018). Converging blockchain and next-generation artificial intelligence technologies to decentralize and accelerate biomedical research and healthcare. *Oncotarget* 9 (5): 5665–5690.
63 Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J.R., and Tchatchouang Wanko, C.E. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. *Business Process Management Journal* 26 (7): 1893–1924.
64 Tambe, P., Cappelli, P., and Yakubovich, V. (2019). Artificial intelligence in human resources management: challenges and a path forward. *California Management Review* 61 (4): 15–42.
65 Chung, S.W., Han, S.S., Lee, J.W., et al. (2018). Automated detection and classification of the proximal humerus fracture by using deep learning algorithm. *Acta Orthopaedica* 89 (4): 468–473.
66 Khan, R.A., Jawaid, M., Khan, A.R., and Sajjad, M. (2023). ChatGPT-reshaping medical education and clinical practice. *Pakistan Journal of Medical Sciences* 39 (1): 301–303.
67 Lu, J., Zhang, W., Hamzei, M., and Jafari, N. (2025). The applications of machine learning mechanisms in the compositions of internet of things services: a systematic study, current progress, and future research agenda. *Engineering Applications of Artificial Intelligence* 147: 110345.
68 Ghafari, R., and Mansouri, N. (2025). Reinforcement learning-based solution for resource management in fog computing: a comprehensive survey. *Expert Systems with Applications* 276: 127214.
69 Majjari, S., Anne, K.R., and George, J. (2023). Deep reinforcement learning (DRL) based data analytics framework for edge based IoT devices latency

and resource optimization. *ACCESS 2023 – 3rd International Conference on Advances in Computing, Communication, Embedded and Secure Systems*.

70 Alsharif, M.H., Mosier, W.A., Alomari, O.A., and Yahya, K. (2020). Supervised machine learning for smart data analysis in internet of things environment: an overview. *Journal of Theoretical and Applied Information Technology* 98 (4): 672.

71 Potharaju, S., Tirandasu, R.K., Tambe, S.N., et al. (2025). A two-step machine learning approach for predictive maintenance and anomaly detection in environmental sensor systems. *MethodsX* 14: 103181.

72 Sharma, A., Balasubramanian, V., and Kamruzzaman, J. (2024). A temporal deep Q learning for optimal load balancing in software-defined networks. *Sensors* 24 (4): 1216.

73 Saadi, A., Abghour, N., Chiba, Z., et al. (2024). Traffic light control using reinforcement and deep learning: a survey and comparison. *Lecture Notes in Networks and Systems* 1123: 410.

74 Garai, S., and Samui, S. (2024). Exploring TinyML frameworks for small-footprint keyword spotting: a concise overview. *2024 International Conference on Signal Processing and Communications (SPCOM*). IEEE.

75 Jiang, Z., Xu, Y., Xu, H., et al. (2024). Semi-supervised decentralized machine learning with device-to-device cooperation. *IEEE Transactions on Mobile Computing* 23 (10): 9757.

76 Zhang, H., Li, M., Yu, H., et al. (2024). Dynamic parameter selection of LoRa edge nodes using reinforcement learning with link prior knowledge. *IEEE Internet of Things Journal* 11 (21): 34420.

77 Sharma, D., Singh, S., Patil, M.R., and Subhan, A. (2024). Medical image processing, disease prediction and report summarization using generative adversarial networks and AIML. In: *2024 2nd World Conference on Communication and Computing (WCONF*) (pp. 1–5). IEEE.

78 Rath, C.K., Mandal, A.K., and Sarkar, A. (2024). Dynamic provisioning of devices in microservices-based IoT applications using context-aware reinforcement learning. *Innovations in Systems and Software Engineering* 1–14. https://doi.org/10.1007/s11334-024-00579-w.

79 Arora, A. (2020). Conceptualising artificial intelligence as a digital healthcare innovation: an introductory review. *Medical Devices: Evidence and Research* 223–230.

80 Duggal, A.S., Singh, R., Gehlot, A., et al. (2021). Infrastructure, mobility and safety 4.0: modernization in road transportation. *Technology in Society* 67: 101791.

81 Ghadi, Y.Y., Mazhar, T., Shah, S.F.A., et al. (2023). Integration of federated learning with IoT for smart cities applications, challenges, and solutions. *PeerJ Computer Science* 9: e1657.

82 Goktas, P., and Grzybowski, A. (2024). Balancing the promises and challenges of artificial intelligence. *Ophthalmology Times Europe* 30–31.

83 Goktas, P., and Grzybowski, A. (2025). Ophthalmology balances the promises and challenges of AI. *Ophthalmology Times* 50.

84 Lee, J. (2020). *Industrial AI. Applications with Sustainable Performance*. Singapore: Springer.

85 Rocha, A., Monteiro, M., Mattos, C., et al. (2024). Edge AI for internet of medical things: a literature review. *Computers and Electrical Engineering* 116: 109202.

86 Qi, Y., and Hossain, M.S. (2024). Harnessing federated generative learning for green and sustainable Internet of Things. *Journal of Network and Computer Applications* 222: 103812.

87 Gopal, G., Suter-Crazzolara, C., Toldo, L., and Eberhardt, W. (2019). Digital transformation in healthcare—architectures of present and future information technologies. *Clinical Chemistry and Laboratory Medicine (CCLM)* 57 (3): 328–335.

88 Goktas, P. (2024). Ethics, transparency, and explainability in generative AI decision-making systems: a comprehensive bibliometric study. *Journal of Decision Systems* 1–29.

89 Goktas, P., and Grzybowski, A. (2025). Shaping the future of healthcare: ethical clinical challenges and pathways to trustworthy AI. *Journal of Clinical Medicine* 14 (5): 1605.

90 Goel, R., and Gupta, P. (2020). *Robotics and Industry 4.0. A Roadmap to Industry 4.0: Smart Production, Sharp Business and Sustainable Development*. Springer Cham.

91 Alotaibi, A., and Barnawi, A. (2023). Securing massive IoT in 6G: recent solutions, architectures, future directions. *Internet of Things* 22: 100715.

92 Gupta, N., Singh, J., Chakraborty, C., et al. (eds.) (2022). *Smart and Secure Internet of Healthcare Things*. CRC Press.

93 Wasatkar, N.N., Chavhan, P.G., and Kolekar, V.K. (2023). IoT and AI-based smart farm: optimizing crop yield and sustainability. In: *Research Trends in Artificial Intelligence: Internet of Things* (pp. 1–17). Bentham Science Publishers.

94 Sarfraz, S., Ali, F., Hameed, A., et al. (2023). Sustainable agriculture through technological innovations. In: *Sustainable Agriculture in the Era of the Omics Revolution* (pp. 223–239). Cham: Springer International Publishing.

95 Bashir, A.K., Victor, N., Bhattacharya, S., et al. (2023). Federated learning for the healthcare metaverse: concepts, applications, challenges, and future directions. *IEEE Internet of Things Journal* 10 (24): 21873–21891.

96 Yang, Y., Wang, H., Jiang, R., et al. (2022). A review of IoT-enabled mobile healthcare: technologies, challenges, and future trends. *IEEE Internet of Things Journal* 9 (12): 9478–9502.

97 Lee, D., and Yoon, S.N. (2021). Application of artificial intelligence-based technologies in the healthcare industry: opportunities and challenges. *International Journal of Environmental Research and Public Health* 18 (1): 271.

98 Kumar, V., Sharma, K.V., Kedam, N., et al. (2024). A comprehensive review on smart and sustainable agriculture using IoT technologies. *Smart Agricultural Technology* 8: 100487.

99 Issa, A.A., Majed, S., Ameer, S.A., and Al-Jawahry, H.M. (2024). Farming in the digital age: smart agriculture with AI and IoT. In: *E3S Web of conferences* (Vol. 477, p. 00081). EDP Sciences.

100 Agrawal, K., Goktas, P., Sahoo, B., et al. (2024). IoT-based service allocation in edge computing using game theory. In: *International Conference on Distributed Computing and Intelligent Technology* (pp. 45–60). Cham: Springer Nature Switzerland.

101 Kalyoncu Atasoy, Z.B., Avery, A., and Goktas, P. (2024). Artificial intelligence-powered nutrition strategies: a focus on vulnerable populations. *Kompass Nutrition & Dietetics* 4 (1): 49–52.

102 Xiao, L., Wan, X., Lu, X., et al. (2018). IoT security techniques based on machine learning: how do IoT devices use AI to enhance security? *IEEE Signal Processing Magazine* 35 (5): 41–49.

103 Bala, B., and Behal, S. (2024). AI techniques for IoT-based DDoS attack detection: taxonomies, comprehensive review and research challenges. *Computer Science Review* 52: 100631.

104 Yagiz, M.A., MohajerAnsari, P., Pesé, M.D., and Goktas, P. (2024). Transforming in-vehicle network intrusion detection: VAE-based knowledge distillation meets explainable AI. In: *Proceedings of the Sixth Workshop on CPS & IoT Security and Privacy* (pp. 93–103).

105 Yagiz, M.A., and Goktas, P. (2025). LENS-XAI: redefining lightweight and explainable network security through knowledge distillation and variational autoencoders for scalable intrusion detection in cybersecurity. *arXiv preprint arXiv:2501.00790*.

106 Bagaa, M., Taleb, T., Bernabe, J.B., and Skarmeta, A. (2020). A machine learning security framework for IoT systems. *IEEE Access* 8: 114066–114077.

107 Ali, M., Naeem, F., Tariq, M., and Kaddoum, G. (2022). Federated learning for privacy preservation in smart healthcare systems: a comprehensive survey. *IEEE Journal of Biomedical and Health Informatics* 27 (2): 778–789.

108 Issa, W., Moustafa, N., Turnbull, B., et al. (2023). Blockchain-based federated learning for securing internet of things: a comprehensive survey. *ACM Computing Surveys* 55 (9): 1–43.

109 Mahmood, N.H., Marchenko, N., Gidlund, M., and Popovski, P. (eds.) (2020). *Wireless Networks and Industrial IoT: Applications, Challenges and Enablers*. Springer Nature.

110 Noor, T.H., Zeadally, S., Alfazi, A., and Sheng, Q.Z. (2018). Mobile cloud computing: challenges and future research directions. *Journal of Network and Computer Applications* 115: 70–85.

111 Ghosh, R.K., Banerjee, A., Aich, P., et al. (2022). Intelligent IoT for automotive Industry 4.0: challenges, opportunities, and future trends. In: *Intelligent Internet of Things for Healthcare and Industry* (pp. 327–352). Cham: Springer.

112 Belliger, A., and Krieger, D.J. (2018). The digital transformation of healthcare. In: *Knowledge Management in Digital Change: New Findings and Practical Cases* (pp. 311–326). Cham: Springer International Publishing.

113 Alshehri, F., and Muhammad, G. (2020). A comprehensive survey of the Internet of Things (IoT) and AI-based smart healthcare. *IEEE Access* 9: 3660–3678.

114 Mohamed, N. (2023). Current trends in AI and ML for cybersecurity: a state-of-the-art survey. *Cogent Engineering* 10 (2): 2272358.

115 Bhandari, G., Lyth, A., Shalaginov, A., and Grønli, T.M. (2023). Distributed deep neural-network-based middleware for cyber-attacks detection in smart IoT ecosystem: a novel framework and performance evaluation approach. *Electronics* 12 (2): 298.

116 Gyamfi, E., Ansere, J.A., Kamal, M., et al. (2022). An adaptive network security system for IoT-enabled maritime transportation. *IEEE Transactions on Intelligent Transportation Systems* 24 (2): 2538–2547.

117 Abdullahi, M., Baashar, Y., Alhussian, H., et al. (2022). Detecting cybersecurity attacks in internet of things using artificial intelligence methods: a systematic literature review. *Electronics* 11 (2): 198.

118 Qu, Q., Hatami, M., Xu, R., et al. (2024). The microverse: a task-oriented edge-scale metaverse. *Future Internet* 16 (2): 60.

119 Moustafa, N., Koroniotis, N., Keshk, M., et al. (2023). Explainable intrusion detection for cyber defences in the internet of things: opportunities and solutions. *IEEE Communications Surveys & Tutorials* 25 (3): 1775–1807.

120 Ashraf, Q.M., Tahir, M., Habaebi, M.H., and Isoaho, J. (2023). Toward autonomic internet of things: recent advances, evaluation criteria, and future research directions. *IEEE Internet of Things Journal* 10 (16): 14725–14748.

121 Alhafnawi, M., Salameh, H.A.B., Masadeh, A.E., et al. (2023). A survey of indoor and outdoor UAV-based target tracking systems: current status, challenges, technologies, and future directions. *IEEE Access* 11: 68324–68339.

122 Rani, S., Kataria, A., Kumar, S., and Tiwari, P. (2023). Federated learning for secure IoMT-applications in smart healthcare systems: a comprehensive review. *Knowledge-Based Systems* 274: 110658.

123 Gill, S.S., Golec, M., Hu, J., et al. (2025). Edge AI: a taxonomy, systematic review and future directions. *Cluster Computing* 28 (1): 1–53.

124 Hemmati, A., Raoufi, P., and Rahmani, A.M. (2024). Edge artificial intelligence for big data: a systematic review. *Neural Computing and Applications* 36 (19): 11461–11494.

125 Mitra, A., Mohanty, S.P., and Kougianos, E. (2024). ToEFL: a novel approach for training on edge in smart agriculture. In: *Proceedings of the Great Lakes Symposium on VLSI 2024* (pp. 657–662).

126 Chen, Y.C., Hsu, S.Y., Xie, X., et al. (2024). Privacy preserving support vector machine based on federated learning for distributed IoT-enabled data analysis. *Computational Intelligence* 40 (2): e12636.

127 Chaves, A.J., Martín, C., and Díaz, M. (2024). Towards flexible data stream collaboration: federated learning in Kafka-ML. *Internet of Things* 25: 101036.

128 Agrawal, S., Sarkar, S., Aouedi, O., et al. (2022). Federated learning for intrusion detection system: concepts, challenges and future directions. *Computer Communications* 195: 346–361.

129 Douaioui, K., Fri, M., Mabroukki, C., and Semma, E.A. (2018). The interaction between Industry 4.0 and smart logistics: concepts and perspectives. In: *2018 International Colloquium on Logistics and Supply Chain Management (LOGISTIQUA)* (pp. 128–132). IEEE.

130 Rane, N.L., Kaya, Ö., and Rane, J. (2024). *Artificial Intelligence*, *Machine Learning, and Deep Learning for Sustainable Industry 5.0*. Deep Science Publishing.

131 Katari, V., Goyal, S., Nigam, V., et al. (2024). A confluence of emerging technologies like IoT, edge & cloud computing, blockchain, industry 4.0 & 5.0, AI & ML toward the realization of eco-friendly supercapacitors. In: *Eco-Friendly Supercapacitors: Design and Future Perspectives in Sustainable and Green Energy Storage Devices* (pp. 163–204). American Chemical Society.

132 Hussein, D.H., and Ibnkahla, M. (2025). Intelligent and autonomous edge slicing for IoT systems. *IEEE Internet of Things Journal* 12 (2): 21210–21224.

133 Baciu, V.E., Braeken, A., Segers, L., and Silva, B.D. (2025). Secure tiny machine learning on edge devices: a lightweight dual attestation mechanism for machine learning. *Future Internet* 17 (2): 85.

134 Mwase, C., Jin, Y., Westerlund, T., et al. (2022). Communication-efficient distributed AI strategies for the IoT edge. *Future Generation Computer Systems* 131: 292–308.

135 Merenda, M., Porcaro, C., and Iero, D. (2020). Edge machine learning for AI-enabled IoT devices: a review. *Sensors* 20 (9): 2533.

136 Dafflon, B., Moalla, N., and Ouzrout, Y. (2021). The challenges, approaches, and used techniques of CPS for manufacturing in Industry 4.0: a literature review. *The International Journal of Advanced Manufacturing Technology* 113: 2395–2412.

137 Anukiruthika, T., and Jayas, D.S. (2025). AI-driven grain storage solutions: exploring current technologies, applications, and future trends. *Journal of Stored Products Research* 111: 102588.

138 Cichosz, M., Wallenburg, C.M., and Knemeyer, A.M. (2020). Digital transformation at logistics service providers: barriers, success factors and leading practices. *The International Journal of Logistics Management* 31 (2): 209–238.

139 Yogi, M.K., Aiswarya, D., and Mundru, Y. (2023). Security for AI and IoT convergence: novel perspectives. *International Journal of Scientific Research in Network Security and Communication* 11 (5): 1–7.

140 Aboualola, M., Abualsaud, K., Khattab, T., et al. (2023). Edge technologies for disaster management: a survey of social media and artificial intelligence integration. *IEEE Access* 11: 73782–73802.

141 Agrawal, K., Goktas, P., Holtkemper, M., et al. (2025). AI-driven transformation in food manufacturing: a pathway to sustainable efficiency and quality assurance. *Frontiers in Nutrition* 12: 1553942.

142 Panahandeh, A., Rabiei-Dastjerdi, H., Goktas, P., and McArdle, G. (2025). Answering new urban questions: using eXplainable AI-driven analysis to identify determinants of Airbnb price in Dublin. *Expert Systems with Applications* 260: 125360.