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Edge Computing for Intelligent Internet of Things: Architectures, Applications, Challenges, and Emerging Trends

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Abstract
The rapid growth of the Internet of Things (IoT) has intensified the demand for computing paradigms capable of supporting real-time data processing, intelligent decision-making, and scalable service delivery. Edge computing has emerged as a key solution by relocating computation and analytics closer to data sources, thereby reducing latency, bandwidth consumption, and dependence on centralized cloud infrastructures. This review provides a comprehensive synthesis of recent advances in edge computing for intelligent IoT, focusing on its foundational concepts, architectural frameworks, intelligent computing techniques, application domains, implementation challenges, and emerging technological trends. The review examines the integration of artificial intelligence, machine learning, federated learning, TinyML, cloud–edge–fog collaboration, and next-generation communication technologies that collectively enhance the efficiency and adaptability of distributed IoT ecosystems. It further discusses the growing adoption of edge computing in smart manufacturing, healthcare, transportation, agriculture, and smart infrastructure, highlighting its contribution to secure, responsive, and data-driven operations. The review also identifies critical challenges, including security, privacy, interoperability, energy efficiency, and regulatory compliance, that continue to influence large-scale deployment. Finally, it outlines emerging research directions involving Generative AI, Digital Twin Networks, 6G communication, open virtualization, and autonomic computing as promising enablers of future intelligent edge environments. Overall, this review offers a consolidated perspective on the evolving landscape of edge computing and identifies key research opportunities for developing scalable, resilient, and sustainable intelligent IoT systems.

Keywords:

- Edge computing, Internet of Things
- Artificial intelligence
- Federated learning
- Intelligent IoT

1. Introduction

Given the rapid expansion of the IoT era, there has been a significant change in the interaction of physical devices, online services, and intelligent systems within different fields. Massive volumes of data in various forms are continuously produced by billions of sensors, actuators, and smart devices, providing significant opportunities for automation, forecasting, and intelligent decision-making. However, the rapid development of the IoT age has revealed some limitations in terms of traditional cloud computing models that can be seen in certain situations when low-latency and real-time response is needed.. Thus, in the current scenario, edge computing has appeared as a new paradigm that brings the computational power closer to the data sources allowing for timely processing and decreasing reliance on centralized cloud infrastructures (Kong et al., 2022; Carvalho et al., 2021).

Edge computing technology has evolved from just data offloading into intelligent distributed computing architecture that supports artificial intelligence (AI) -enabled IoT applications. Performing computations, storage, and analytics at edge devices and nodes will yield faster response time, reduced network congestion and improve overall system resilience. In real-time scenarios such as intelligent urban infrastructure, intelligent manufacturing, health care systems, intelligent industry automation, and intelligent transportations, these immediate decision-making capabilities could affect system reliability and human safety (Quy et al., 2023; Yang et al., 2021).

The technological developments of recent times make it crystal clear that the age of convergence of edge computing with AI, machine learning, 5G communication networks, software-defined networking, virtualization technologies, and lightweight intelligent models is here. Such convergence makes edge nodes capable of performing complex analysis, predictive maintenance, anomaly detection, resource management, etc., without continuous data transfers to distant cloud computing nodes. Furthermore, the new generation of distributed computing paradigms, including fog computing, serverless computing and Function-as-a-Service (FaaS), are increasing the capabilities of distributed intelligent systems, making them more scalable, flexible, and able to utilise resources in a better manner in heterogeneous IoT environments (Bourechak et al., 2023, Ghaseminya et al., 2025).

Even though these improvements have been made, there are still a number of technical and operational problems that hinder the deployment of intelligent edge-enabled IoT systems. There are still a number of challenges to overcome for large-scale deployment, such as resource-constrained edge devices, interoperability issues, security vulnerabilities, privacy preservation, dynamic service orchestration, workload balancing and energy efficiency. Additionally, the complexity of distributed architectures demands comprehensive management solutions that can handle different types of applications and their unique needs while guaranteeing reliability, trustworthiness, and sustainability within interconnected ecosystems (Veeramachaneni, 2025; Carvalho et al., 2021).

Over the last several years, many surveys have focused on a certain part of the edge computing, such as smart city applications, AI, communication technologies, or edge architecture. As the technologies of intelligent IoT, edge intelligence, advanced networking and emerging decentralized computing paradigms are quickly converging, however, it is time for an updated and comprehensive synthesis of current knowledge. In current literature, often only a single technological aspect is highlighted, and the combined effect of such technologies in intelligent IoT ecosystems is rarely discussed (Zhou et al., 2022; Kong et al., 2022).

This review, therefore, extensively discusses the basic architectures of edge computing, enabling technologies, intelligent computing techniques, practical applications, key implementation issues, and the latest research trends for intelligent IoT. This review is designed to provide a comprehensive insight into the state of the art of edge computing by incorporating recent advancements from various interdisciplinary research fields, as well as identify knowledge gaps and future research directions (Veeramachaneni, 2025; Bourechak et al., 2023; Ghaseminya et al., 2025).

2. Foundations of Edge Computing for Intelligent IoT

With the advent of edge computing, a paradigm change is needed in the design of intelligent Internet of Things (IoT) systems in order to process huge amounts of data at the edge of the network. The cloud-computing paradigm has been the foundation of IoT applications for a long time, providing scalable storage and computational power. The fast growth of connected devices has, however, uncovered the problems of a centralized approach to processing—namely that it results in higher communication latency, too high a bandwidth footprint and a lower responsiveness for time-sensitive services. Edge computing is a solution to these challenges, enabling data to be processed at the edge of the network and decisions to be made in real-time by geographically distributed edge nodes (Angel et al., 2021; Gkonis et al., 2023).

The development of edge computing is strongly related to the development of distributed computing paradigms, including the convergence of cloud, fog and edge. Edge computing isn't a replacement for cloud computing, but rather an addition to it, creating a hierarchical computing continuum where computations can be dynamically allocated based on latency, resource availability, and application priorities. In this spectrum, the cloud platform is still used for bulk analytics and long-term data storage, while fog nodes are closer to the devices to perform intermediate processing, and edge devices perform latency-critical operations at the edge of the network. This co-operative architecture enhances the scalability, resilience and resource consumption in the heterogeneous IoT ecosystems (Angel et al., 2021; Gkonis et al., 2023).

One of the defining traits of the modern edge computing is the use of artificial intelligence (AI) in a distributed computing system. With the development of machine learning, deep learning, and lightweight inference models, edge devices can conduct intelligent analysis without the need to constantly send raw data to central servers. Enhanced edge systems using AI can help identify anomalies, make autonomous decisions, make predictions for future maintenance and prioritize the protection of user privacy by keeping data where it belongs. Thus, the integration of AI with edge computing empowers edge nodes to become more intelligent and autonomous computing devices that can adaptively and autonomously operate (Hua et al., 2023; Mohammed & Raheem, 2025).

Intelligent edge systems have been further enhanced by recent advancements in communication technologies. The high-speed 5G networks have greatly improved data transmission speed, connection between devices, and reliability of the network, and with the arrival of 6G, ultra-low latency, distribution of intelligence, and seamless integration of distributed AI services are expected to be realized. The communication breakthroughs enable efficient collaboration between the edge, fog and cloud layers, enabling real-time applications like autonomous cars, industrial automation, immersive digital environments and smart health care. At the same time, virtualization technologies and Function-as-a-Service (FaaS) models have brought about a new level of flexibility, which allows for dynamic resource allocation and scalable services deployment across heterogeneous computing infrastructures (Ghaseminya et al., 2025; Omheni et al., 2025).

Together, these technological advances lay the groundwork for adaptive, scalable and resilient IoT ecosystems. The new possibilities offered by modern IoT systems, with their distributed computing architectures, AI-powered intelligence, sophisticated networking technologies, and cloud-edge collaboration, have been a huge asset. These principles will remain crucial as intelligent applications continue to grow and evolve, allowing for the creation of efficient, secure, and sustainable edge computing infrastructures that can support the next generation of connected digital environments (Mohammed & Raheem, 2025; Omheni et al., 2025). The computing paradigms enabling intelligent IoT vary in terms of where they are processed, how much processing power they have, latency and what they are used for. Table 1 illustrates the different levels of intelligence (cloud, fog, edge, and device) in the IoT computing continuum and how these levels can complement each other to enable scalable and responsive applications.

Table 1. Comparative Characteristics of Computing Paradigms for Intelligent IoT

Computing Paradigm	Processing Location	Main Function	Key Advantage	Sources
Cloud computing	Centralized remote data centres	Large-scale storage, model training, and historical analytics	High computational and storage capacity	Angel et al. (2021); Gkonis et al. (2023)
Fog computing	Intermediate nodes between cloud and devices	Regional data aggregation, filtering, and service coordination	Balanced latency and processing capability	Angel et al. (2021); Mohammed and Raheem (2025)
Edge computing	Gateways, base stations, and local servers	Real-time analytics, inference, and local decision-making	Low latency and reduced bandwidth use	Hua et al. (2023); Gkonis et al. (2023)

Device-level intelligence	Sensors, embedded devices, and microcontrollers	Immediate sensing, lightweight inference, and actuation	Fast response and improved data privacy	Hua et al. (2023); Mohammed and Raheem (2025)
Cloud–edge–fog continuum	Distributed across all computing layers	Dynamic task allocation and coordinated service execution	Scalability, flexibility, and workload optimization	Ghaseminya et al. (2025); Omheni et al. (2025)

3. Architectures and System Design of Edge-Enabled Intelligent IoT

The design of edge-enabled Internet of Things (IoT) systems has become quite different to cope with the increased demands for low latency, scalability and intelligent service delivery. Edge computing, which is different from traditional cloud-based systems, places the computing, storage, and networking resources in a hierarchy of multiple locations, where data is processed near its source. Decentralization helps lower the delay in communication, relieve backbone traffic, and improve the responsiveness of the system, especially when it comes to real-time applications such as automation, healthcare, and autonomous vehicles. Therefore, current-edge architecture tends to rely more on decentralization while still being capable of functioning alongside the cloud architecture (Cao et al., 2020; Kong et al., 2022).

Intelligent edge architecture is made up of three closely related layers. They include the device layer, edge layer and cloud layer. Devices are comprised of sensors, actuators, wearable devices, and embedded systems, which gather data. At the edge layer, localized analytics, temporary data storage, filtering, and intelligent inferences are done using the local edge servers/edge gateways. Finally, at the cloud layer, computationally intensive tasks such as model training, historical data analysis and resource management are done. The multi-layered architecture helps to partition tasks according to their execution requirements such as latency and computation complexity and, thus, makes the system more efficient (Cao et al., 2020; Kong et al., 2022).

The recent breakthroughs in AI have significantly contributed to edge architecture by allowing intelligent resource orchestration and self-management. Intelligent edge systems provision computing resources according to network conditions and characteristics of workload as well as predicting service placement. On the other hand, the microservice-based architecture improves the flexibility of the systems since IoT applications that are complex in nature are broken down into small modules. These modules are light and independently deployable. These architectures offer advantages for scalability, quick deployment of services, efficient use of diverse computing resources, and the NextG communication environment (Zeb et al., 2023; Ramamoorthi, 2023).

Cloud-edge orchestration is also a critical element in intelligent design of IoT systems. Cloud and edge platforms work in tandem to distribute workloads as necessary for each application. Latency sensitive inference tasks are performed at edge nodes, and the computationally intensive tasks of model training and large scale analytics are performed in cloud environments. This co-ordinated effort ensures better service continuity, dynamic workload migration and adaptive quality of service management between geographically distributed infrastructures. Therefore, hybrid cloud-edge architectures offer more flexibility and resilience in operation than stand-alone computing architectures (Ramamoorthi, 2023; Zeb et al., 2023).

Security has also become an important part of designing edge architectures since distributed infrastructures present many more attack surfaces in a variety of devices and communication methods. To protect sensitive IoT data, authentication, access control, encrypted communication, trusted execution environments and continuous threat monitoring are becoming a part of the edge platforms. New architectural concepts also investigate recursive and structurally symmetric network designs to improve the network's resilience against cyber threats, while also preserving its scalability and interoperability. Such security-aware architectural principles are believed to be crucial to ensure the success of future intelligent IoT ecosystems running over increasingly complex distributed environments (Fortino et al., 2022; Teymoori & Ramezanifarkhani, 2026). Generally, the architecture of an intelligent edge-enabled IoT system is a coordinated sequence of data and service flows between sensing devices, edge nodes, fog and cloud platforms. A simplified layered view of the architecture of how data are processed progressively from IoT devices to cloud based services is given in figure 1.

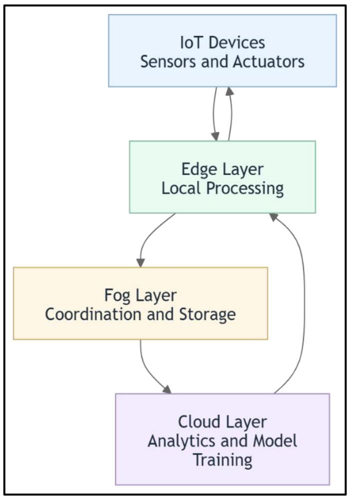

Figure 1. Layered Architecture of Edge-Enabled Intelligent IoT

4. Intelligent Computing Techniques at the Edge

With the advent of intelligent computing techniques on the edge, IoT infrastructures have evolved from traditional architectures to autonomous and adaptive systems able to process data locally, with low latency. Intelligent edge computing also allows real-time inference and decision-making at or close to the data sources, minimizing the communication overhead and enhancing the responsiveness, as opposed to traditional cloud-based analytics. The combination of artificial intelligence (AI) and machine learning (ML) with distributed computing has boosted the capabilities of edge devices, enabling them to perform predictive analytics, anomaly detection, object recognition, and context-aware services in various IoT applications (Modupe et al., 2024; Bablu & Rashid, 2025).

The computational intelligence of modern edge systems is largely based on two technologies: Machine learning and Deep learning. With the development of lightweight neural networks, model compression and hardware acceleration, more and more complex AI models can be deployed to devices with limited resources. The models facilitate continuous monitoring and decision-making, reducing the dependence on cloud-based infrastructure. Hence, it can be said that Edge AI is playing an important role in aiding latency-critical applications such as industrial automation, intelligent surveillance, medical diagnosis, and smart transport, where quick action is essential to improve efficiency and safety (Chinta, 2024; Bablu & Rashid, 2025).

Federated learning (FL) has become one of the most impactful techniques for privacy-preserving intelligent systems in distributed IoT settings. Instead of uploading raw and sensitive data to a centralized server, federated learning enables each edge device to train a machine learning model on its own, only sending model parameters to the server for global aggregation. This collaborative learning paradigm has the potential to greatly improve data privacy, lower the amount of network traffic and enable compliance with regulations in areas where sensitive information is involved. In recent years, there have been significant advances in architecture that further enhance the efficiency of cloud-edge-end collaboration, such as lightweight communication protocols, secure aggregation mechanisms, and adaptive model synchronization strategies, making federated learning increasingly feasible for large-scale intelligent IoT deployments (Li et al., 2024; Zhan et al., 2025).

With the increasing need of privacy aware intelligent healthcare, use of secure federated learning, coupled with Explainable Artificial Intelligence (XAI), has further boosted the adoption. By integrating privacy-preserving learning with interpretable AI models, healthcare professionals can benefit from understanding the model's predictions while still ensuring the privacy of patient information. In the same vein, clustering-based federated deep learning methods have shown better disease management as well as prediction accuracy as they were able to organize the distributed learning processes in a more efficient way at the edge devices. These developments show that intelligent edge computing can enhance, at the same time, the analytical performance, transparency, and privacy protection in critical healthcare environments (Raza, 2023; Yang & Li, 2025).

Another major breakthrough is the advent of TinyML, which allows inference of machine learning on extremely resource-constrained microcontrollers and embedded devices. The model quantization, pruning and optimization provided by TinyML reduces the computation complexity, memory usage and energy cost without compromising the predictive accuracy of models. This ability helps make battery-operated devices, such as sensors, wearables, and remote monitors, sustainable in terms of edge intelligence, when under strict resource constraints. Edge AI, federated learning, and TinyML are complementary methods of intelligent computing that are reshaping next generation IoT systems by providing scalable, secure, energy-efficient and real-time intelligence at the network edge (Echchidmi & Bouayad, 2026; Chinta, 2024). Complementary methods are combined in intelligent edge systems to balance the predictive performance, privacy, communication overhead, and hardware limitations. Table 2 provides an overview of the different intelligent computing approaches that can be used at the edge and how they can contribute to secure, responsive and resource efficient IoT applications.

Table 2. Intelligent Computing Techniques Used in Edge-Enabled IoT

Technique	Core Function	Major Benefit	Representative Application	Sources
Edge machine learning	Performs prediction and classification near data sources	Low-latency inference and reduced cloud dependence	Fault detection and predictive maintenance	Modupe et al. (2024); Chinta (2024)
Edge deep learning	Executes neural network models on edge platforms	Supports complex pattern recognition	Medical imaging and intelligent surveillance	Bablu and Rashid (2025); Chinta (2024)
Federated learning	Trains models locally and shares model updates	Protects raw data and reduces data transfer	Distributed healthcare and mobile IoT	Li et al. (2024); Zhan et al. (2025)
Explainable federated learning	Combines distributed learning with interpretable predictions	Improves privacy, transparency, and trust	Smart healthcare decision support	Raza (2023); Yang and Li (2025)
TinyML	Deploys compressed models on microcontrollers	Low memory use and energy-efficient inference	Wearables and remote sensing	Echchidmi and Bouayad (2026)

5. Applications of Edge Computing in Intelligent IoT

As a key technology, edge computing has emerged to facilitate real-time data processing, decentralized intelligence, and autonomous decision-making, thereby paving the way for the implementation of intelligent Internet of Things (IoT) applications in various sectors. Edge-enabled IoT systems can decrease latency, boost operational reliability, and minimize the bandwidth usage, which is ideal for mission-critical environments where timely response is key. Digital transformation in the industrial, healthcare, agricultural, and transportation sectors is rapidly progressing with the advent of edge computing, artificial intelligence (AI), advanced communication networks, and cyber-physical systems (Choudhry et al., 2024; Gatti et al., 2023).

Edge computing is one of the main enablers of Industry 4.0 and plays an important role in smart manufacturing, such as predictive maintenance, automated quality inspections, robotic coordination, and intelligent production management. With continuous analysis of sensor data from industrial equipment, manufacturing systems can identify anomalies, optimize production schedules and minimize downtime without completely relying on centralized cloud infrastructures. This local intelligence helps improve production efficiency and facilitates adaptive and resilient manufacturing environments (Choudhry et al., 2024; Gatti et al., 2023).

Intelligent edge computing has also had great impact on Healthcare, real-time patient monitoring, wearable medical devices and emergency response systems have all benefitted. Medical sensors placed at the network edge can quickly process the physiology data and timely detect the abnormal condition, without compromising patient privacy by reducing data transfer with the outside world. In a like manner, intelligent transportation systems (ITS) use edge computing to help traffic optimization, vehicle-to-everything (V2X) communication, and autonomous vehicles. The use of unmanned aerial vehicles (UAVs) is also a key extension of the capabilities of edge-enabled services, as it allows for aerial surveillance, disaster assessment, emergency logistics, and infrastructure inspection, as well as intelligent coordination in dynamic environments (Mbarak et al., 2026; Choudhry et al., 2024).

Another emerging application domain is agriculture, where edge computing helps to enable precision agriculture and climate-smart agriculture. Soil, crop, irrigation and environmental parameters are continuously monitored with distributed IoT sensors, UAVs and AI based analytics. These data could be processed in the edge nodes, thereby enabling farmers to take decisions in real-time concerning their irrigation schedule, pest control, fertilization, and crop monitoring. At the same time, it will reduce the cost associated with communication and minimize energy consumption. Furthermore, the application of UAVs that is highly automated, along with 5G technology and wireless communication, contributes to agricultural automation and sustainable food production under changing environmental conditions (Majumdar et al., 2025; Vinothagan et al., 2026).

In addition to these applications, edge computing is gaining popularity in smart infrastructure and environmental resource management. Intelligent water systems consist of edge computing enabled sensors and wireless communication networks (WCNs) through the application of UAVs in order to perform water quality monitoring, leakage detection, and energy savings. This enables data processing to happen locally and detect system anomalies quickly, as well as to enable autonomous resource management with minimal reliance on cloud services. Together these different applications show that edge computing has matured to become a flexible and powerful technological backbone for secure, efficient, and sustainable real-time services in increasingly interconnected digital environments (Radhakrishnan, 2024; Mbarak et al., 2026).By allowing for fast data processing and analysis locally, autonomous control and minimizing reliance on the cloud, edge computing can facilitate a variety of intelligent IoT applications. The key Application Areas are summarized in Figure 2.

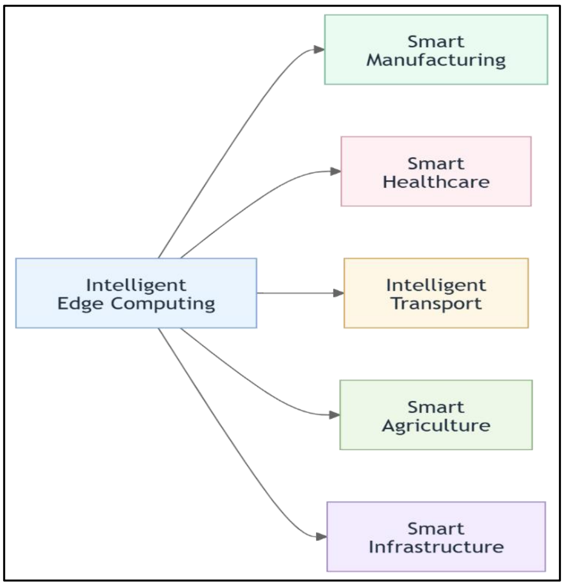

Figure 2. Major Applications of Edge Computing in Intelligent IoT

6. Challenges and Open Issues

Even though edge computing has made great strides in the development of intelligent Internet of Things (IoT) systems, multiple technical, operational and regulatory issues remain before it can be widely used. Unlike traditional cloud-based architectures, edge infrastructures are decentralized, contain a variety of hardware platforms, and have a mix of communication protocols and geographically distributed resources, all of which add to a more complex system management challenge. The ability for smooth communication between edge nodes and the provision of high-quality services under varying network conditions is a long-standing challenge for intelligent IoT ecosystems (Mishra et al., 2024; Mrabet & Sliti, 2025).

Security, privacy and trust are the most important issues in edge empowered IoT environments. Edge nodes can be attractive targets for cyberattacks, unauthorized access, data manipulation and distributed denial of service (DDoS) attacks, since computation is taking place outside of centralized data centers. From healthcare systems to industrial processes and smart city infrastructures, sensitive information is gathered and must be well-protected during its entire lifecycle. As a result, secure authentication methods, encrypted communication protocols, trusted execution environments (TEEs), access control policies, and data provenance techniques are becoming more widely considered as key elements of resilient edge computing systems. Trust between the heterogeneous devices and distributed services is also crucial for guaranteeing secure and reliable collaboration between interconnected edge networks (Mishra et al., 2024; Mrabet & Sliti, 2025).

Energy efficiency, sustainable resource utilization, is another big challenge. Though edge computing helps to reduce the communication cost through computation of the information on the edge, the various edge devices, being always on, could result in high computing cost when combined. In order to maintain a balance between computing efficiency and environmental sustainability, intelligent workload scheduling, energy-efficient resource allocation, adaptive task offloading, and efficient hardware utilization are essential. As per recent researches, the integration of artificial intelligence, IoT analytics, and edge computing is highly instrumental in optimizing energy consumption in smart environments (Rojek et al., 2025; Tchakoute & Tadonki, 2026).

Absence of standards and regulatory measures further contribute to the challenges of using edge computing in different industries. Interoperability issues may arise because of differing security requirements, communication protocols and technology vendors. In addition, changes in legal regulations related to data management, data transfer across borders, privacy concerns and ethical application of artificial intelligence are always an issue and require extensive regulatory guidance for safe and responsible use. Interoperability, regulation and sustainability will thus be key for future edge computing-based IoT ecosystems, where standard architectures and internationally acknowledged frameworks for governance will be indispensable (Sani, 2025; Mrabet & Sliti, 2025).

For dealing with these challenges, a multidisciplinary approach will be necessary, particularly focusing on secure system architecture, intelligent resource management and sustainable computing practices. The next generation of edge computing platforms will have to meet multiple performance, scalability, security, privacy and environmental requirements, all the while being able to support ever more complex and heterogeneous IoT ecosystems. Researchers, industry players, and policy makers alike will need to collaborate and continue to do so to address these open challenges and promote the widespread adoption of intelligent, trustworthy, and sustainable edge computing infrastructures (Tchakoute & Tadonki, 2026; Sani, 2025). While edge computing has the potential to enhance IoT responsiveness and decentralisation, security, energy, interoperability, and governance are obstacles to its widespread adoption. As mentioned before, the main issues, their impact on edge systems and key mitigation areas found in the literature are presented in Table 3.

Table 3. Major Challenges and Mitigation Priorities in Intelligent Edge Computing

Challenge	**Primary Cause**	**System-Level Impact**	**Mitigation Priority**	**Sources**
Security vulnerabilities	Distributed nodes and expanded attack surfaces	Data breaches, service disruption, and device compromise	Strong authentication, encryption, and continuous monitoring	Mishra et al. (2024); Mrabet and Sliti (2025)
Privacy and trust	Local processing of sensitive and heterogeneous data	Unauthorized disclosure and reduced user confidence	Privacy-preserving analytics and trust management	Mishra et al. (2024)
Energy consumption	Continuous computation and large-scale device deployment	Higher operational cost and environmental impact	Energy-aware scheduling and efficient hardware	Rojek et al. (2025); Tchakoute and Tadonki (2026)
Interoperability	Diverse devices, vendors, and communication protocols	Limited integration and difficult service coordination	Common standards and open architectural interfaces	Sani (2025); Mrabet and Sliti (2025)
Regulatory compliance	Differing rules for data governance and AI use	Legal uncertainty and restricted cross-domain deployment	Harmonized policies, accountability, and audit mechanisms	Sani (2025)

7. Emerging Trends and Future Research Directions

Today, the convergence of various technologies, such as artificial intelligence (AI), next-generation communication networks, autonomous system management and advanced virtualization technologies are increasingly driving the evolution of edge computing. In the future, with the ever growing world of smart Internet of Things (IoT) ecosystems, edge infrastructures are envisioned to be not only locally data-processing but also self-adaptive and self-aware. These advancements are designed to meet the skyrocketing demand for ultra-low latency, massive device connectivity, smart resource management, and seamless service provisioning in highly distributed networks (Mohsin et al., 2025; Sheraz et al., 2024).

Among the most promising research directions is its integration in edge-enabled 6G communication systems with the use of Generative AI. Generative AI is able to optimize and adapt network configurations dynamically, automate resource allocation, generate synthetic data for training, and assist in intelligent decision making across distributed infrastructures – things that traditional AI models cannot do as well, if at all. Combined with the features of 6G networks, such intelligent systems can deliver ultra-reliable and low-latency communication and enable autonomous orchestration of edge services for future smart cities, industrial automation, and immersive digital environments and connected healthcare applications (Mohsin et al., 2025; Sheraz et al., 2024).

Another important trend is the use of Digital Twin Networks (DTNs), virtual representations of physical edge infrastructures, communication networks and IoT environments. By resonating sensors and actuators with digital systems, digital twins can continuously update the virtual model, enabling network operators to simulate workloads, predict failures and measure performance, and optimize resource usage, before making operational changes. Regarding the future possibilities of digital twins within the sophisticated 6G ecosystem, which consists of dynamic workloads and various devices, Digital Twins combined with artificial intelligence (AI) and edge computing will bring many possibilities for predictive maintenance, intelligent planning, and resilient services (Sheraz et al., 2024).

Also, the evolution of virtualization and infrastructure management is expected to affect the future of edge computing. In this age of distributed computing environments, people are looking at the possibility of using open-source virtualization software and other infrastructure solutions due to their benefits and flexibility. Virtualization technologies provide dynamic workload relocation, deployment of applications in containers, resource sharing between cloud-edge infrastructures, thus creating intelligent IoT systems that are more agile and resilient. Such transformations can help accelerate the innovation process through reduced dependence on proprietary ecosystems (Bhatia & Gabhane, 2025).

In the longer term, there is a direction of travel in intelligent edge ecosystems called autonomic computing. Autonomic computing is drawn from the biological systems that are self-managing, and adds self-configuration, self-optimization, self-healing and self-protection features to distributed computing environments. Autonomic edge systems, powered by AI, will be able to handle resource management, failure detection, and security threat mitigation, and optimize performance, with minimal human intervention. The capabilities are expected to become basic traits of future, intelligent IoT infrastructure, and form a highly resilient, scalable, and sustainable edge computing infrastructure, supporting increasingly complex digital applications (AYOMIDE et al., 2026; Mohsin et al., 2025). It is anticipated that future edge computing systems will integrate next-generation connectivity on the edge with autonomous resource management, digital twins and generative intelligence. As seen in Figure 3, the most significant trends that will define the evolution of intelligent edge-enabled IoT ecosystems are pointed out.

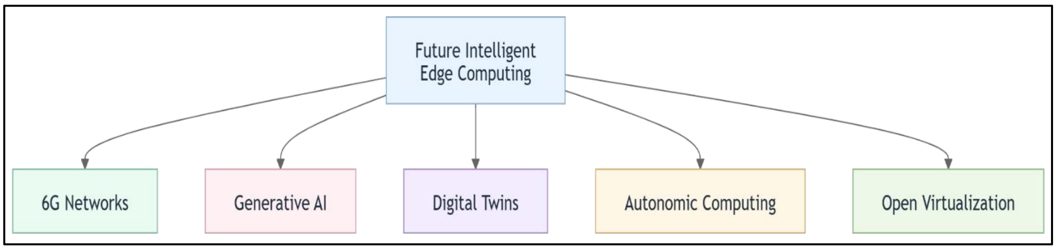

Figure 3. Emerging Trends in Intelligent Edge Computing

8. Comparative Analysis and Research Gaps

Though the literature shows that there is great advancement in the development of edge computing frameworks for intelligent Internet of Things (IoT) systems, the area in which there are still great differences is in the architecture design, scalability, security, and application focus. While conventional edge architectures are mostly focused on minimizing latency and distributed data processing, more recent frameworks feature artificial intelligence (AI), cloud-edge-fog cooperation, and cross-domain resource orchestration for adaptive and data-intensive applications. Multi-layer and collaborative architectures offer overall more flexibility and resilience compared to standalone edge deployments, especially in heterogeneous IoT scenarios (Timisică et al., 2025; Trakadas et al., 2022).

New research also shows that AI is going distributed with capabilities built across cloud, edge and end devices as opposed to residing in a single layer of the computing stack. This development will further increase the real-time analytics, automate decision making, and ensure continuity of service while improving scalability of the system. Likewise, cloud-edge-fog collaboration has gained significant promise for healthcare, industrial automation, and smart city applications, leveraging the advantages of proximity and latency in conjunction with cloud-based resources.Similarly, collaborative cloud-edge-fog models have demonstrated substantial promise in supporting applications such as healthcare, industrial automation, and smart cities, leveraging the benefits of proximity and latency alongside the cloud's resources. However, interoperability issues, differences in hardware architectures, and difficulty with orchestration have limited the application of these cooperative architectures (Ortiz et al., 2026; Rahman et al., 2026).

However, there are still a number of research challenges that hamper the development of intelligent edge computing. Many available works consider specific aspects of the architecture or specific application fields separately and with only minor focus on architectures that allow for solving multiple aspects, such as scalability, security, sustainability, explainability and autonomous resource management. In addition, there are still a lack of standardized methods for evaluation and universally accepted models for architecture, which makes it difficult to objectively compare different edge computing solutions. Future research should thus focus on integrated architectures that leverage AI, on standardised interoperability frameworks, on energy-efficient resource orchestration, and on cross-domain validation to enable the deployment of scalable, secure, and intelligent IoT ecosystems (Trakadas et al., 2022; Timisică et al., 2025).

Conclusion

Edge computing is a paradigm that has gained significant traction in recent years, with the promise of creating intelligent Internet of Things (IoT) ecosystems by moving computation, analytics and decision making closer to the source of data. In this review paper, the evolution of the edge computing architecture, the integration of artificial intelligence, federated learning, and TinyML, and their comprehensive role in providing support to secure, low-latency, and resource-efficient IoT applications have been discussed. It also illustrated the role of edge computing in driving innovation across various industries, such as manufacturing, healthcare, transportation, agriculture, and smart infrastructure, as well as lowering communication overhead and enhancing operation responsiveness. Many of these developments notwithstanding, there are still security, privacy, interoperability, energy efficiency, and regulatory standardization issues that are hindering widespread adoption. New innovations such as Generative AI, Digital Twin Networks, 6G connectivity, open virtualization and autonomic computing will continue to boost the intelligence, scalability and resilience of next-generation edge-enabled systems. In conclusion, the integration of distributed intelligence and advanced networking techniques is revolutionizing the design of future IoT ecosystems. Future research efforts should focus on architecture integration, framework standardization, sustainability of resource management, and trustworthy artificial intelligence in order to provide for a scalable and adaptive edge computing infrastructure for intelligent digital environments.

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