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Review

Artificial Intelligence and Edge Computing for Sustainable Smart Water-Safety Monitoring in Low-Resource Communities: A Critical Review

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Abstract

Poor water quality monitoring and delayed responses to pollution remain major challenges in low-resource areas. Traditional methods of monitoring water and wastewater resources are ineffective because they take a long time to report contamination. Therefore, this critical review aims to examine how a combination of artificial intelligence (AI) and edge computing can comprehend decentralised, real-time water quality monitoring, even in areas with limited infrastructure and internet, constrained maintenance capacity, and shortages of skilled personnel. To our knowledge, this study is a first-of-its-kind integrated framework that showcases edge AI architectures and refers to specific operational, societal, and infrastructural limitations in the water, sanitation, and hygiene (WASH) sector. The synthesis clearly shows that the implementation of edge AI techniques has the capability to improve global water quality through immediate pollution detection, disaster forecasting, and automatic filter or alarm response without the need for cloud infrastructure. The examples given from developing countries support this statement by demonstrating that the technologies are low-cost and implementable in the long term. The problem of sensor calibration, data quality, and energy efficiency was identified as the most important implementation challenge. There is enough evidence of pilot-scale tests, but long-term validation of the technology in field trials is needed. The authors also present future research directions, such as the integration of AI, edge computing, machine learning, and IoT, and open-source edge frameworks. Edge AI systems provide promising avenues for decentralised water safety surveillance in low-resource communities in real time and can support the sustainable development goals of the United Nations through the realisation of clean water and sanitation for all.

Keywords: edge AI; water quality monitoring; Internet of Things (IoT); sensor; machine learning; pollution; real-time monitoring

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1. Introduction

Globally, the water crisis has persisted for centuries, with people having no or limited access to treated, safe drinking water services [1]. This contributes to persistent waterborne disease burdens, such as cholera, dysentery, and typhoid fever, which remain among the central factors affecting human health in poor regions, contributing to high morbidity and mortality rates [2,3]. Waterborne diseases are brought on by enteric infections, which can be caused by bacteria, viruses, or parasites. Some enteric bacterial pathogens include

Salmonella spp., *Escherichia coli*, *Campylobacter* spp., *Shigella* spp., *enterohemorrhagic E. coli,* and *E. coli* O157:H7, *Cryptosporidium parvum*, *Isospora belli* (now known as *Cystoisospora belli*), *Giardia lamblia*, and *Cyclospora cayetanensis*, which are the major common enteric protozoa linked to waterborne diseases. More recently, the enteric virus hepatitis E has been inferred to cause waterborne diseases. Abubakar [4] emphasised the importance of improving water-quality monitoring systems to support United Nations Sustainable Development Goal (SDG) 6, which aims to ensure safe drinking water and adequate sanitation for all by 2030. There is, therefore, a need for countries to step up efforts to protect freshwater sources and improve water quality monitoring.

Typical monitoring systems (such as manual sampling and laboratory testing) are discrete, time-consuming, expensive, and unable to detect real-time pollution events [5]. Hence, common sampling methods for the detection and enumeration of faecal indicator organisms and pathogens are becoming less accurate over time due to several factors, including a lack of skilled personnel, poor infrastructure, and financial constraints. Notably, the newest innovations in artificial intelligence (AI) and machine learning (ML) have made it much easier for sensors to detect poor water quality [6,7]. They can read the sensors and the data that were recorded in the past. Edge computing is a decentralised computing approach in which computations and model inference occur at or near the device rather than sending information to remote cloud servers for processing. In this review, the system was deemed an edge computing system if the main AI inference or decision-making was performed locally on embedded hardware such as Raspberry Pi (Raspberry Pi Ltd., Cambridge, UK), Jetson Nano (NVIDIA Corporation, Santa Clara, CA, USA), ESP32 (Espressif Systems, Shanghai, China), or microcontrollers with TinyML capabilities, regardless of whether synchronisation with the cloud was possible at any time. In edge computing, data are processed locally, and no remote cloud is involved, solving the problems of connectivity and latency, thus allowing real-time decisions in decentralised systems [8,9]. The AI and edge computing hybrid, known as edge AI, has confirmed the idea of forming low-power, low-cost monitoring systems that are capable of working independently in areas with low connectivity; however, their application in water surveillance is still emerging [10].

Recent innovations related to artificial intelligence (AI), machine learning (ML), and IoT have the potential to make water monitoring a near-real-time, data-intensive, and future-oriented task [6,11,12]. However, the concerns regarding conventional cloud architectures concerning connectivity and computational resources are problematic when implemented in rural communities. Edge computing can essentially decentralise the cloud for data processing, offering a possible solution. In addition, it allows for decentralised monitoring without cloud dependence. When combined with AI (edge AI), it may make inferences, perform local anomaly detection, and generate responses autonomously while minimizing energy and bandwidth consumption [13]. Studies on ML and cloud integration have indicated that these technologies can detect turbidity and microbial contamination in water sources and trigger early warning signals with automated actions, such as data filtering or public announcements/alerts [8,9]. The adoption of these technologies in the rural water and wastewater sectors is scarce. Despite the progress made, several studies have described the adaptation of cloud computing, IoT, and edge computing in resource-poor areas; however, their integration into water, sanitation, and hygiene (WASH) systems and stable scaling remain uncommon [10,14–16]. Some studies address the implementation of AI- or IoT-based water-system monitoring; however, the available literature lacks synthesis [17–21].

For the purposes of this review, limited-resource areas encompass rural, peri-urban, and underserved regions where at least one of four potential constraints, lack of electric-

ity, lack of internet connectivity, lack of lab capabilities, and lack of qualified personnel, prevents the deployment of traditional water quality monitoring systems. Additional constraints can be added to this list, such as a lack of maintenance capabilities, a lack of funds for purchasing equipment and replacing sensors, a lack of rapid transport from the testing site to central laboratories, and poor governance/data management practices. All these problems are quite common in developing countries, but similar issues could emerge in high-income countries as well, particularly in remote communities. In this review, low-resource areas refer to operational conditions rather than geographic or economic classification.

In previous review papers, the role of AI, IoT, cloud computing, or edge computing has been addressed separately [17,22]. But most studies have focused mainly on the algorithms or sensors and not on the evaluation of the deployment architecture and technoeconomic viability of the models in addition to robustness, cybersecurity, and suitability for low-resource WASH infrastructure. The present review paper differs in that it considers all these aspects together and highlights research needs. It presents a technology and system-oriented critical review that synthesises integrated AI models, edge computing architectures, sensing technologies, and related operational constraints to improve the design of smart water-safety monitoring in limited-resource settings. This review focuses on smart water monitoring as a water-safety function, with the primary objective of the early detection of contamination events that pose direct public health risks and contribute toward achieving Sustainable Development Goal 6 (clean water and sanitation).

2. Data Acquisition

2.1. Search Strategy

This review paper conducted a structured critical literature review to identify recent progress in edge AI and intelligent water quality monitoring, with a focus on low-resource and rural WASH service delivery. Literature between 2015 and 2025 was sourced from the following databases: Google Scholar, PubMed, EBSCOhost Online Research Databases, IEEE Xplore, MEDLINE, ISI Web of Knowledge, Scopus, and Web of Science. This search was done in February 2026. The year 2015 is considered appropriate because studies on IoT-enabled AI monitoring and edge computing emerged after 2015. Online-first publications were considered for indexing. The search strategy included keywords such as ("edge AI" OR "AI" OR "cloud AI" OR "edge computing") AND ("water quality monitoring" OR "water safety") AND ("IoT" AND "sensors" OR "real-time surveillance" OR "real-time monitoring") AND ("low-resource settings" OR "limited-resource area" OR "rural community"), AND ("WASH"). A targeted search was also conducted to identify studies on microbial water quality monitoring, federated learning, autonomous systems, and sensing technologies. As shown in Figure 1, a total of 1248 papers were initially obtained. After removing duplicates (n = 312), the reference list of the papers (n = 936) was screened to identify relevant articles. At the time of screening, 44 papers were identified as being irrelevant to the scope of this study based on predefined inclusion criteria. A total of 118 papers met eligibility criteria, and from these, the most relevant (37 studies) were chosen for discussion in this study based on their direct relevance to edge AI, IoT, or cloud/edge systems in water-quality monitoring applications; sufficient methodological and deployment information; and non-redundancy with other datasets.

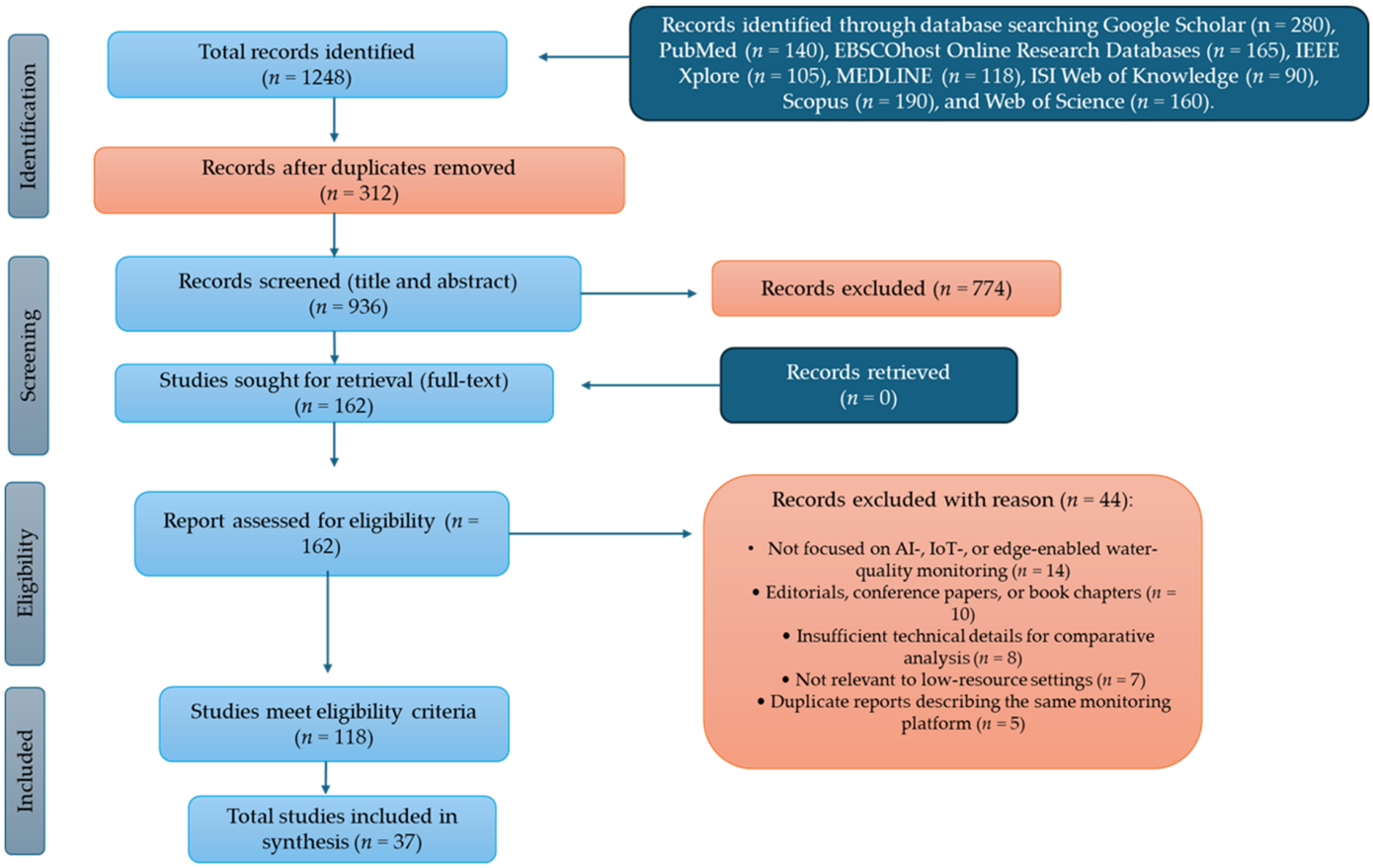


Figure 1. Process of literature selection for structured critical review.

2.2. Inclusion and Exclusion Criteria

The review prioritised studies that addressed artificial intelligence (AI); Internet of Things (IoT); edge computing; machine learning; cloud AI; real-time water quality monitoring; sensing technology; connectivity architecture; and low-resource, rural, and peri-urban settings. Only publications in English were considered. The study included peer-reviewed journal articles, technical reports, conference papers, and grey literature. Duplicate and inaccessible full texts were excluded from this study. In addition, articles unrelated to the water domain, such as those on biomedical imaging, and those lacking technical details were excluded. As this study is not a meta-analysis or systematic review, but a structured critical review, quantitative polling or statistical aggregation of results was not performed. A synthesis of the literature was conducted for the selected studies.

2.3. Data Extraction

The variables extracted from each study comprised information regarding publication (author and year), study settings, sensor typology, communication technology, computing technology (cloud, edge, or hybrid), use of AI or machine learning techniques, hardware platform used, measured parameter, performance parameters of the system, applicability to low-resource settings, and the strengths and weaknesses of the system. If there were multiple papers about the same water monitoring platform or dataset, only the most comprehensive paper was used.

3. Evolution of Water Quality Monitoring

The need for increased temporal resolution and rapid water contamination detection has revolutionised water quality monitoring from manual sampling and laboratory-based

assessments to fully automated and intelligent systems [6,23]. The evolution of water quality monitoring (timeline depicted in Figure 2) has progressed from manual sampling and laboratory-based testing in the 1960s [5], through Internet of Things (IoT)-based sensing in the 2000s [24] and cloud-based artificial intelligence (AI) analytics in the 2010s [25], to edge AI in the 2020s [10,26]. This evolution reflects a broader paradigm shift from compliance-driven sampling towards risk-based, continuous surveillance. The performance overlays indicate improvements in latency, cost, autonomy, and suitability of the technology, thus facilitating real-time decentralised water safety surveillance, which is essential in low-resource settings. Traditional monitoring, which depends on central regulatory compliance, cannot capture real-time pollution spikes associated with precipitation events, agricultural runoff, or sanitation failures [5,27]. Hence, these methods were designed for regulatory reporting rather than rapid outbreak prevention. These methods mostly depend on laboratory resources, skilled technicians, and stable logistics that are often limited in most African and South Asian rural communities, where contamination events require immediate responses [28,29]. Although emerging technologies such as edge computing have some advantages, such as reduced latency and low connectivity, they introduce new constraints, such as limited computational capacity, model compression, and sensor maintenance calibration in harsh environmental conditions [29,30]. Furthermore, Internet of Things (IoT)-supported monitoring systems have emerged with their continuous sensing and remote data acquisition capabilities [14]. Accordingly, IoT monitoring systems were initially cloud-centric, which meant that they needed a power supply, network reliability, and high bandwidth [31,32]. Studies have indicated problems with data delays and poor infrastructure or loss of frequent monitoring, especially during critical contamination seasons [30,33]. Therefore, edge-AI systems must operate under these challenging conditions.

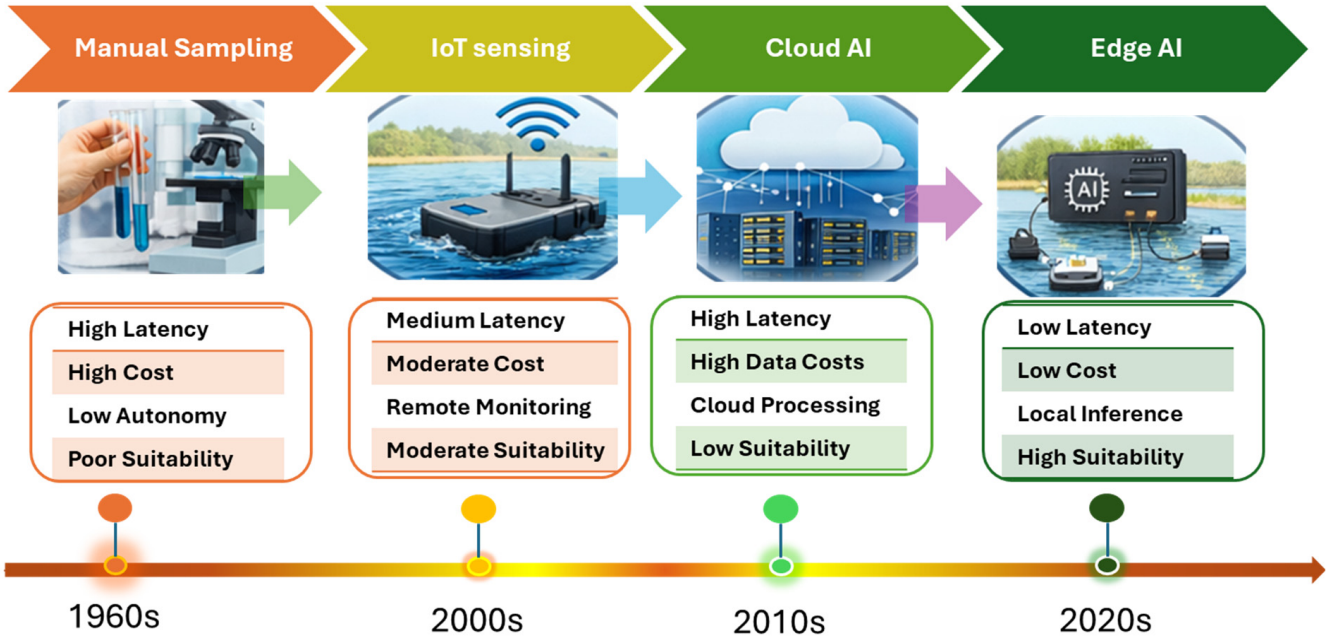


Figure 2. Evolution of water-quality monitoring architectures starting from laboratory-based water quality monitoring to IoT sensing, Cloud AI and edge AI. The timeline outlines the evolution of technology towards monitoring systems, with emphasis on edge AI, as it shows suitability for use in low-resource settings.

Figure 2 presents the progression of technology trends in water quality monitoring rather than the timeline specific to low-resource contexts. While cloud AI architectures dominate in high-income countries with abundant resources, edge AI is clearly the

most appropriate architecture for low-resource settings due to its features, such as local inference, cost-saving communications, low latency, and ability to operate intermittently. Thus, Figure 2 illustrates the advantages of using edge AI in low-resource WASH application scenarios.

The new phase of development is the integration of AI-based predictive analytics with Internet of Things (IoT) platforms. Machine learning and deep learning have improved anomaly detection, prediction of turbidity and microbial contamination, and pollution source identification [34,35]. However, the main limitation is that most AI systems render processes on remote servers, which results in poor functioning under disconnection times, which are common in low-resource settings [15]. The strengths and weaknesses of these surveillance techniques are outlined in Table 1. The transition to edge AI has been rapid owing to these deficiencies; it is based directly on electronic devices. Studies have shown that edge AI nodes can accurately operate on low-power microcontrollers that obtain energy from solar panels deployed intermittently [14,33]. This system can easily be implemented in locations that have no laboratory facilities, maintenance capacity, or data management systems [14,16,33]. This has led to the establishment of smart water-safety architectures conceptualised for context-relevant and resilient deployment to promote the wellbeing of underserved communities. Despite these advances, gaps remain in the lack of microbial datasets, insufficient integration of monitoring frameworks, and limited implementation studies in limited-resource communities.

Table 1. Strengths and weaknesses of water-quality monitoring techniques.

Water-Quality Monitoring Technique	Strengths	Weaknesses	References
Traditional laboratory (manual sampling)	High analytical accuracy and validation	Inherently time-consuming; it requires significant human resources and is not appropriate for real-time response.	[5]
IoT-based	Continuous sensing and remote collection of data	Highly dependent on connectivity and power supply; cybersecurity risk; it requires frequent sensor maintenance; and data loss due to network outages.	[24]
Cloud-based AI	Large-scale predictive analytics and centralised data integration	Inherent high latency, security risks, costly transmission of data, and rural limitations.	[25]
Edge AI	Real-time local inference, minimal dependency on networks, and enhanced autonomy	Inherently limited computing capabilities, sensor issues, and model sustainability.	[26]

4. Why Low-Resource Settings Require New Monitoring Architectures

Structural barriers in low-resource communities make conventional water-quality monitoring architectures impractical. As defined in Section 1, low-resource settings are characterised by several limitations in infrastructure and operations that reduce the efficacy of water quality monitoring using traditional techniques. These limitations may include unstable power supply, unreliable communication, limited access to laboratories, a shortage of skilled personnel, an inability to conduct maintenance operations, and limited finances. Altogether, these constraints necessitate locally autonomous and efficient decision-making. The limited availability of reagents, transport, and other resources in rural African communities makes laboratory-based sampling slow and costly, as it depends on skilled technicians [33]. Sampling methods cannot rapidly identify pollution and, in turn, require corrective action rather than delayed centralised reporting [36]. Internet of

Things (IoT)-embedded systems have been invented to solve the problem of continuous sensing [24]. However, many early deployments depended on cloud servers for analytics, requiring stable electricity and reliable bandwidth, both of which were often unavailable in underserved regions [34,37]. Rural water-centric studies found that disconnected or power-outaged cloud-linked sensors were responsible for repeated downtimes and data gaps observed during contamination events [38]. The additional factor of data governance inadequacy creates problems in the archiving, sharing, and usability of water quality data.

Microbial detection implies measuring microbes and their DNA through microbiological, molecular, and biosensor assays (e.g., *Escherichia coli*, *Vibrio cholerae*, or antimicrobial resistance genes (ARGs)). Prediction of the risk of microbes implies estimating the likelihood of microbial contamination based on some surrogates of physicochemical or environmental parameters like turbidity, temperature, precipitation, conductivity, or dissolved oxygen. Despite the ability to serve as a means of early warning, the predictive models do not prove microbial contamination and should thus complement microbiological tests. In contrast to that case, cloud-AI frameworks have gained predictive potential; however, they are still connected similarly and do not fit well into low-density networks [39]. This clearly portrays the existing architectural failure, in which designs that were tailored to urban settings and adapted to low-resource communities were simply not a good fit. The edge AI architectural framework provides a novel, context-appropriate alternative. By executing inference on the device, it decreases bandwidth, performs under unstable input connections, and sustains low-power operations compatible with a solar microgrid [40]. The newness of this model lies in its decentralised intelligence: cloud services are removed and replaced by citizens' own management to maintain the ongoing implementation of decision-making in the management of scarce resources.

5. Smart Water-Safety Monitoring System

Water quality monitoring has undergone a paradigm shift, moving from centralised and reactive systems to proactive, digital intelligence-distributed and network-based systems, owing to recent technological advancements [41,42]. The features of the smart monitoring architecture include the integration of sensing, communication, and computing to enable the prompt detection of pollution events and evidence-based decision-making [31]. To date, sensor data have been processed locally using onboard machine learning algorithms. Such a system saves data transmission and becomes more durable, as it can still operate in areas with weak connectivity and low power supplies. Table 2 lists the current advances in Internet of Things (IoT), AI algorithms, edge computing, implementation limitations, and sustainability in one review on decentralized water-quality monitoring in low-resource communities, as well as the components of the edge AI system, which form the basis of the integrated framework presented in this study.

Table 2. Summary of key studies on AI, IoT, and edge-based water-quality monitoring systems, highlighting methods, technology, application, limitation, and novelty.

Reference Studies	Primary Focus	Detection	Technology Used/Covered	Performance (Accuracy/R^2)	Used Hardware	Deployment Maturity	Setting (Coverage of Low-Resource Setting)	Application	Limitations	Novelty	Critical Gap
[14]	IoT- and AI-based water-quality monitoring systems	Physicochemical parameters	Machine learning and IoT integration for pollutant detection	Accuracy = 99.5%	Not clearly specified	Literature review	Urban and semi-urban monitoring networks (limited coverage)	Continuous water monitoring	Technical models addressed in isolation only; deployment constraints addressed sparingly	Analyses of AI–IoT architectures, addressing constraints but lacking a strong rural edge AI framing	Not extensively addressed: Edge deployment, governance, cost and long-term validation
[43]	Deep learning for microbial contamination detection	Microbial contaminants	Autoencoders and CNNs for anomaly detection	R^2 = 0.982	Edge-cloud IoT devices	Laboratory and smart-city applications	Laboratory-based test networks and urban smart-city water networks (not covered)	Anomaly real-time detection	Limited scalability and energy analysis	Focuses on real-time, on-device inference for bacterial detection, but remains limited to urban areas and labs	Energy efficiency, scalability and field deployment were not addressed
[44]	AI prediction for water quality forecasting	Physico-chemical parameters (e.g., turbidity, connectivity)	RNN, LSTM, and hybrid machine learning models	Accuracy > 90%	No hardware included	Modelling studies	Theoretical and modelling framework	Prediction for long-term surface water quality	Did not include hardware, communica-tion, or cost concerns	Advances forecasting accuracy, but edge computing is not included	Not mentioned: Hardware, communication infrastructure and implementation
[18]	Edge computing for environmental monitoring	Environmental conditions (e.g., water quality)	Edge–cloud hybrid models	No common metric reported	Edge and satellite-connected nodes	Conceptual review	Urban and agricultural environment (not covered)	Real-time monitoring for ESG governance	Did not discuss edge computing, socioeconomic integration, or community-based edge AI governance for WASH monitoring	Focuses on advancing broadband for real-time environmental monitoring in urban settings, but not for WASH in low-resource areas	Community engagement, governance, and WASH application were not addressed
[45]	Edge-enabled IoT for decentralised water treatment	Wastewater treatment (effluent)	Edge nodes and distributed networks	No common metric re-ported	Low-cost edge device	Industrial im-plementation	Industrial, municipality, and field (limited coverage)	Wastewater treatment plants	Focus on high-resource contexts.	Proposes an IoT infrastructure for a wastewater treatment plant, utilizing low-cost, low-power hardware	Rural deployment, affordability and sustainability were not addressed

Table 2. *Cont.*

Reference Studies	Primary Focus	Detection	Technology Used/Covered	Performance (Accuracy/R^2)	Used Hardware	Deployment Maturity	Setting (Coverage of Low-Resource Setting)	Application	Limitations	Novelty	Critical Gap
[46]	Federated edge learning for wastewater risk management	Effluent indicators	Federated learning (AWSFA, Bi-LSTM)	$R^2 \geq 0.93$; Accuracy = 99.28%	Centralised WWTP system	Simulation/ WWTP	Wastewater treatment plant (not covered)	Real-time risk prediction	No implementation cases in low-income countries	Proposes an improved federated learning in the detection of risk	Field validation and low-income deployment were lacking
This Review	Integration of AI and edge computing for smart water safety in low-resource communities	Microbial and physicochemical parameters	System-wide integration of AI models, TinyML, edge devices, IoT sensors, and community participation frameworks	Comparative synthesis of reported performance metrics	Edge nodes (TinyML, solar-powered system)	Synthesises laboratory, pilot and field evidence	Rural, peri-urban, and low-resource settings (Sub-Saharan Africa, South Asia) (primary focus)	Real-time decentralised water quality monitoring	Limited field-validated studies on edge AI and limited dataset from rural areas for AI training	Provides an integrated conceptual and operational framework linking technology, cost, and SDG 6 alignment for sustainable water monitoring and African deployment	Highlights gaps in robustness, calibration, cybersecurity, technoeconomic feasibility, governance and validation

A critical comparison of existing studies in Table 2 indicates that most current development remains in peri-urban areas, urban areas, laboratory-based environments, or industrial environments. While several studies reported high predictive accuracy of water quality and anomaly detection, the majority did not evaluate long-term performance under the operational constraints and characteristics of low-resource areas [14,44]. Ayad et al. [43] demonstrated microbial anomaly detection efficacy utilising deep learning models. However, energy consumption and sensor maintenance requirements were not considered. Similarly, Marozva et al. [44] achieved improved forecasting accuracy using Long Short-Term Memory (LSTM)-based approaches, but the absence of hardware integration limited practical deployment. These evidence-based results suggest that the performance of an algorithm alone is insufficient for suitability determination of water surveillance in rural and resource-limited settings. Due to disparities in datasets, evaluation measures, environmental settings, and reporting techniques, direct quantifiable comparisons cannot be easily made. As a result, the results have to be seen as trend indicators but not performance benchmarks. Another important observation is the persistent separation between sensing analytics and the governance framework. Previous studies usually focused on single technological components, while successful deployment in resource-limited settings requires integration of sensing systems, edge computing technologies, community participation, and a sustainable maintenance plan. Consequently, future research should prioritise system-level validation rather than isolated algorithms. In addition, this review is meant to be a synthesis of the evidence at hand and not a validated deployment model. Current pilot projects show that the technical implementation of edge AI is feasible. However, large-scale validation under varied climatic and socioeconomic conditions is still lacking.

5.1. The Use of Artificial Intelligence in Surveillance of Water Quality

Naturally, traditional centralised monitoring arrangements are reactive rather than proactive, and they tackle pollution incidence after it occurs because they are focused on correcting the past [47]. A lack of up-to-date data also leads to delays across the public health sector, such as issues with treatment plants (e.g., boil water recommendations or processing plants). Despite physicochemical parameters, microbial contamination remains one of the major causes of freshwater-related disease outbreaks globally. Pathogens such as *Salmonella* spp., *E. coli*, and *Vibrio cholerae* are the most common threats in rural communities [48]. The delay in detecting these microorganisms can contribute to outbreaks of dysentery, cholera, and other waterborne diseases. Hence, the use of AI in real-time surveillance enables rapid detection of these microbial hazards, with recent studies showing that real-time AI systems and on-site monitoring can reduce detection times [18,26,43], thereby protecting public health, especially for vulnerable populations. However, in low-resource settings, such systems are rare because of connectivity constraints and high costs. Accordingly, despite regulatory compliance, traditional surveillance is still too slow, overly capital-intensive, and too centralised to satisfy the requirements of vulnerable communities. Evidently, new edge computing and AI technologies have the potential to provide affordable, automated, and continuous monitoring systems that will be a breakthrough in overcoming the drawbacks of the previously used traditional methods [33,45]. Even though the literature provides promising results for edge AI, its applicability to rural communities remains unverified.

5.2. The Need for AI Edge Computing in Water Quality Monitoring

Artificial intelligence (AI) technology has rapidly become a breakthrough technology in environmental monitoring, providing capabilities that are not available using traditional laboratory and sampling methods [14]. In water quality management, AI enables com-

puterised data interpretation, variance identification, and predictive modelling, thereby allowing decision-makers to act before pollution incidents get out of control [49]. Recently, the emergence of low-cost sensors and high-throughput Internet of Things (IoT) devices has facilitated the constant dissemination of real-time water data, providing fertile ground for AI-based analytics [19]. We summarised the benefits of edge computing and AI models in Figure 3.

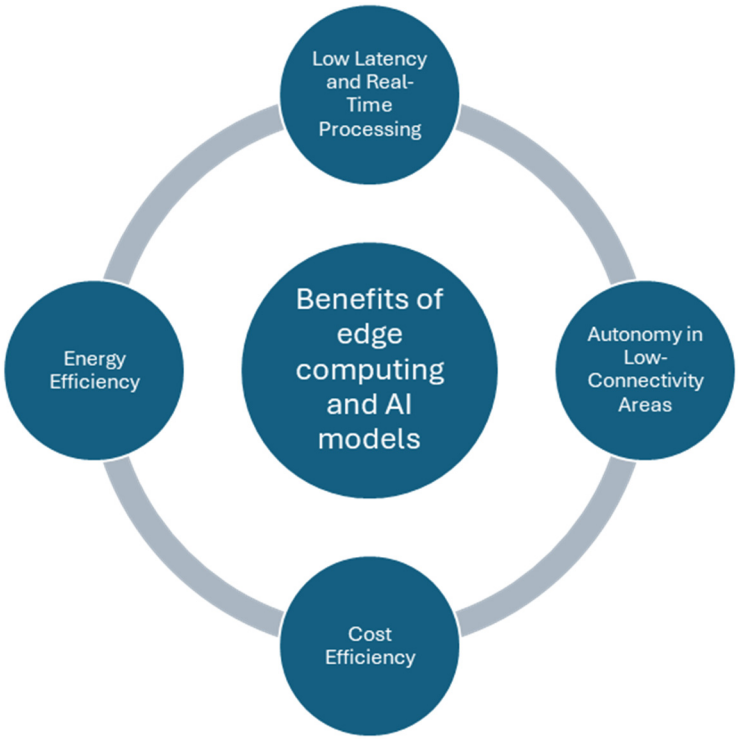


Figure 3. Benefits of edge computing and AI models.

Water quality datasets are multidimensional (covering, for example, physical, chemical, and biological parameters) and are affected by noise and nonlinearity [50]. In addition, there has been an increase in AI models being used in the detection and prediction of microorganism contamination [43]. Recent studies have shown that artificial intelligence (AI) algorithms, especially machine learning (ML) and deep learning (DL) algorithms, can assess the relationships between variables such as turbidity, rainfall, temperature, dissolved oxygen, and microbial indicators such as *E. coli* and faecal coliform [7]. An example of this can also be seen in the work of Jena et al. [51], who demonstrated the application of a random forest model to Indian surface waters to achieve more than 90% accuracy during laboratory validation in predicting bacterial contamination using turbidity, precipitation, and temperature as predictor variables. This predictive capacity can improve early warning for fast-action plan deployment to prevent the use of contaminated water before laboratory confirmation tests are conducted. Despite the improvements made in predictive modelling, reported studies demonstrate significant progress in prediction accuracy, whereas there is limited evidence for large-scale implementation.

6. Model Robustness, Uncertainty, and Scalability of Edge AI Systems

Although the combination of AI and edge computing technologies has shown great promise in water-quality monitoring applications, the effectiveness of the system depends on its robustness, capacity for dealing with uncertainties, and scalability to different environmental settings. These features are not well-investigated in many of the papers reviewed here, where predictive performance measures like accuracy, precision, recall, or

R^2 coefficient are mostly considered without considering model performance over time. Some recent review articles point out that the focus on predictive performance rather than operational performance is a key characteristic of many water monitoring studies using AI methods [14,44].

6.1. Model Robustness

Robustness of the AI model involves its ability to provide reliable performance despite changes in the environmental and operational context in which the model operates. The water-quality monitoring systems installed in natural environments have to deal with sensor drift, biofouling, seasonality, hydrology changes, communication gaps, and data loss. All of these factors affect the statistical properties of the input data and thus reduce the robustness and the accuracy of the predictions made by the AI model. The majority of the papers reviewed in this section used their models on datasets obtained through controlled laboratory experiments or covering limited spatial and temporal scales, which does not allow for conclusions to be drawn about the performance of the model under field conditions [43,45].

6.2. Uncertainty Quantification

Uncertainty quantification, an issue that has not been adequately addressed in the literature, is yet another aspect that should be considered. Most studies do not provide any form of uncertainty assessment in relation to their models and simply provide deterministic outputs with no indication of how confident they are about their predictions. This is because uncertainties could emanate from the inaccuracies in data collection through sensors, incomplete datasets, variations in the environment, assumptions made by models, and limitations of algorithms used. If the predictions generated from these models are not accurate, there could be issues like false alarms or even missing contamination events.

6.3. Scalability

Additionally, some scalability issues were observed by the authors which could pose constraints on implementing edge computing in low-resource areas. Most of the current systems are either laboratory prototypes or pilot-scale implementations which involve a limited number of sensors and minimal data volumes. Scaling up these systems for regional- or national-level monitoring programmes poses several technical issues like diverse sensor platforms, interoperability in communication protocols, increased computation demands, data synchronization, and maintenance of the edge computing systems distributed across the region. Moreover, many of these low-resource areas suffer from inconsistent power supply, unreliable internet connectivity and lack of technical expertise, which could limit the implementation of these AI-based monitoring systems. Therefore, the future of scalable edge computing systems should be characterized by energy-efficient machine learning models, energy harvesting techniques, modular designs and standard communication protocols [46,52].

7. Key Components of Edge AI for Autonomous Water Quality Monitoring

Edge AI-based automated water quality monitoring ensures the required efficiency by establishing a robust interlinkage of various systems, including edge devices, sensors, AI models, and communication frameworks, which work together to establish efficient, reliable, real-time, and decentralised operations. Their unique role in data sensing, processing, and decision-making in real-time, independent of the central cloud, makes them legitimate partners. For example, a workable edge AI water monitoring system should first be built on the principles of durability, energy efficiency, interoperability, and low maintenance, especially in low-resource contexts [14,16]. In such topologies, sensor nodes are water-quality

measurement devices that present both water pulsing and sensor networks, thus involving edge devices where local inference acts on water quality data integration [18,31]. Weighted networks, which transmit processed results or alerts to decision-makers nationally or globally, are lightweight communications [44]. Additional components are needed to include these variables and form a distributed system that functions even in the absence of power.

7.1. Sensor Networks for Water Quality Monitoring

Effectiveness of edge AI water monitoring systems can be ensured through the deployment of a sensor network that collects real-time data from different sources of water with respect to spatial distribution. The sensors are necessary to capture physicochemical, biological, and environmental parameters that are critical to water safety, such as turbidity, pH, dissolved oxygen, temperature, and bacterial contamination [53,54]. In resource-limited areas, sensor networks must be cost-effective, energy-efficient, and robust enough to withstand changes in temperature, humidity, and pollution while ensuring consistent performance. A recent study revealed that multi-mechanism hybrid sensor arrays composed of optical, electrochemical, and biosensor types can detect a wider range of water quality changes than single-parameter sensors [55]. As shown in Table 3, various sensors are used in water quality monitoring; hence, their site-specific suitability must be assessed for use in rural areas.

Table 3. Variations in sensor technology for edge-AI-enabled monitoring and their suitability in low-resource areas.

Typology of Sensors	Examples	Parameters	Edge Compatibility	Suitability in a Limited-Resource Area	References
Physical sensors	Optical (UV-Vis), remote sensing, backscatter sensors, and MEMS-based probes	Turbidity, colour, temperature, and conductivity sensors	Low-moderate	Moderate (fouling challenge)	[53]
Chemical sensors	Electrochemical, ion-selective sensors, fluorescence, and nanosensors	Nitrates, pH, phosphates, heavy metals, salinity, toxins, and organic pollutants	Moderate-high	High (potable, sensitive but costly)	[56]
Biosensors	Enzyme sensors, immunosensors, molecular platforms, and microfluidic chip sensors	Pathogens, toxins, microbial genes, AMR markers, and nutrients	Moderate	Moderate (stability issues, maintenance, and need for lab support)	[54]

Note: The edge suitability criteria in low-resource areas include the following: "High" denotes technologies that can be deployed easily in low-resource settings with little infrastructure available; "Moderate-High" denotes technologies that are suitable most of the time with some restrictions; "Low-Moderate" denotes technologies that require more infrastructure, maintenance, or skilful deployment; and "Moderate" means that the technology can be deployed, although it requires some form of maintenance or improvements.

Despite significant advances in the development of biosensors [53,54], various limitations remain before these technologies can be widely adopted. Most of these biosensors demonstrated high analytical sensitivity under laboratory conditions, but their performance decreases when exposed to biofouling and temperature fluctuations. These limitations are particularly important in rural communities and low-resource settings, where technical support is limited. There is a need to assess their performance to adequately evaluate calibration frequency, maintenance requirements, or replacement cost. Therefore, future sensor

development should prioritise robustness, self-calibration capacity and affordability over sensitivity alone. Consequently, studies on sensors should also shift beyond optimising performance to include long-term operation.

Bacterial contamination is the primary cause of waterborne diseases in some underdeveloped regions, such as cholera, typhoid, and dysentery [57]. Hence, emerging biosensors offer significant opportunities for microbial surveillance. With edge AI technology combined with biosensors and microfluidic chips, it is possible to obtain real-time information on pathogen detection and antimicrobial resistance (AMR) with increased sensitivity for detecting the presence of disease-causing markers, such as coliforms, *E. coli*, and *Vibrio cholerae*. Yin et al. [58] demonstrated rapid CRISPR-based biosensors with an advanced microprocessor for detecting *E. coli* at a concentration of 3.6×10^1 CFU/mL in 30 min without laboratory intervention; however, their deployment in low-resource areas may be limited due to the requirements of these specialised biosensors. Similarly, Khurshid et al. [34] reported the implementation of a machine learning and Internet of Things framework that was deployed at Rawal Dam in a rural area of Pakistan for monitoring water quality indices and predicting bacterial contamination. Using an Artificial Neural Network (ANN) model, the framework achieved a maximum accuracy of 99.5% on an independent test dataset, enabling the prediction of bacterial contamination before its occurrence. Reported performance of these technologies may not necessarily translate into improved public health outcomes since there are still limitations related to deployment, maintenance issues, and adoption of technology by communities. Likewise, Munawar et al. [59] utilised convolutional neural networks (CNNs) in the analysis of heterogeneous datasets with an accuracy of 91% in the prediction of floods, thereby enabling timely interventions during adverse weather conditions. Together, these studies illustrate a trade-off between analytical sensitivity and field deployability, highlighting the need for affordable biosensing systems integrated with AI architecture. Wang et al. [60] combined the Internet of Things (IoT) with machine learning algorithms for the monitoring of environmental parameters. These findings suggest that the utilisation of advanced sensors and IoT technology not only increases the detection speed but also improves the precision of the application. Integration of these technologies with edge AI may allow real-time monitoring of microbial hazards and other chemical hazards in water sources, thereby minimising the reliance on laboratory-based monitoring and reducing the effects of disease outbreaks.

While there is widespread availability of physicochemical sensors that can be used in the field, microbial sensing poses many challenges. Almost all microbial biosensors need to have access to specific reagents, samples prepared and stored at precise temperatures, as well as regular calibration. As a result, edge computing currently relies on physicochemical sensing or predicting microbes through indirect methods. However, new developments in portable biosensors and CRISPR technology have the capability to change that. Sensor networks in very remote or rural settings are still limited by power, calibration, and endurance [28,29,61]. For instance, with the deployment of AI-based calibration and data aggregation approaches, sensor nodes can autonomously identify and correct inaccurate readings and rectify them [22]. Additionally, a study by Tatiraju et al. [23] revealed that there is a 35% reduction in data redundancy and a 40% improvement in the accuracy of anomaly detection with the aid of machine learning-based WSNs, thus improving reliability. Therefore, sensors are critical for the edge AI scheme.

7.2. Impact of Sensor Calibration in the Accuracy of AI Predictions

Calibration of sensors is essential for ensuring the effectiveness of AI-based water-quality monitoring systems due to the reliance of machine learning algorithms on the accuracy of input data. While numerous studies recognize the need for sensor calibra-

tion [14,45], few assess its effect on the accuracy of prediction by the algorithms. In field operations for extended periods of time, sensors can be affected by biofouling, environmental variability, ageing, and sensor drift, thus causing systematic errors in measurements. These errors will affect machine learning models' performance, leading to reduction in the algorithm's generalizability and the generation of false predictions. Therefore, machine learning algorithms such as ANNs, random forest, CNNs, and LSTM networks might perform worse when working with inaccurate sensor data [43,44]. Calibration errors have especially important consequences in edge AI applications in resource-scarce environments because their maintenance and recalibration may be hampered by a lack of technical expertise, inconsistent power supply, and limited laboratory capacity [45]. New methods such as adaptive calibration algorithms, sensor fusion, transfer learning, and uncertainty-aware models are potential means of overcoming sensor drift and achieving more reliable predictions in real-world conditions [46]. Consequently, future research should include calibration procedures in addition to the results of AI predictions and study the effects of different calibration frequencies on prediction accuracy and uncertainty.

7.3. Data Security and Integrity

Ensuring the confidentiality of water quality data maintains public trust and aligns policies with effective water quality management [62]. AES-256 encryption, SSL/TLS, and blockchain-based data authentication are increasingly used as security measures to protect integrity and provide transparency in decentralised systems [63]. In addition, adaptive sampling and real-time compression techniques minimise bandwidth usage while preserving decision-critical information [40]. A hybrid architecture of local edge intelligence and occasional cloud synchronisation provides the best balance between data security, energy savings, and reliability [64]. In conclusion, a resilient and secure network infrastructure is a promising platform for scaling up edge AI water monitoring architectures, with decentralised systems that are permanently connected, open, and responsive, always adapting to the changing environment for sustainable safe water.

8. Research Gaps in Edge AI for WASH

Although edge AI has the potential to dramatically reduce operational costs, actual costs for microbial monitoring remain largely unquantified, limiting discussions on cost implications and the identification of cost-reducing AI methods [29,30,33]. Substantial knowledge and experience gaps remain regarding the non-technical factors that influence optimal sensor network performance in low-resource settings. AI algorithms trained in high-resource settings may not generalise to highly heterogeneous rural water sources, and locally based models typically perform better for monitoring edge devices. In addition, microbial datasets that are suitable for AI model training in rural communities are scarce. Hence, this has restricted the design and validation of the microbial and chemical prediction models across diverse freshwater environments. Long-term sustainability is also hindered by maintenance challenges, low technical capacity, and over-the-air updates on low-power devices [7,10,26,65]. The trust and agency of local communities in modelling edge devices that surveil their water systems are often overlooked during deployment. This creates a risk that trained AI models in Europe, China, or North America may not accurately represent microbial dynamics in tropical freshwater systems. To date, research remains fragmented, with technologies, governance and community engagement usually investigated independently. Hence, this fragmentation limits the development of a sustainable, integrated, and scalable framework for field deployment.

9. Practical Barriers and Limitations of Edge AI for Water Quality Monitoring

The widespread deployment of advanced AI for water quality monitoring in low-resource settings is hindered by a series of technological, environmental, and socioeconomic factors. From a public health perspective, delays or failures in detecting microbial contamination have severe consequences, particularly in remote areas with limited resources. While edge AI offers early detection, its accuracy depends on the accuracy of the sensor system and the effectiveness of microbiological and physicochemical validation incorporated into existing frameworks for water monitoring, risk assessment, and management. Identifying these barriers will lead to more targeted research and the development of fair and sustainable frameworks. A notable limitation of existing studies is the evaluation of technical performance without including socioeconomic and governance limitations. However, such technology for smart monitoring will depend on community acceptance, support from the governance, and maintenance of the technology deployed. Despite improvements in low-resource settings, several monitoring approaches remain ineffective because of infrastructure, financial, and socioeconomic constraints (summarised in Table 4) [29,33]. The performance of cloud-based systems in remote areas is poor because of network connectivity issues and high data transmission costs [37,65].

Table 4. Barriers to edge AI in smart water-quality monitoring and potential solutions.

Domain	Examples	Causes	Potential Solution	References
Technical constraints	Sensor drift, model size, and limited computational resources	Rain runoff (increased turbidity and sediment load) or agricultural activities	Use corrosion-resistant and biodegradable materials (such as silicon-coated circuits and graphene composites); model compression and self-calibration sensors	[29,30,55,66]
Environmental factors	Biofouling, temperature variation, humidity, and particle pollution	Formation of biofilm, deposition, and degradation of electronics	Protective coatings, sealed housings, and waterproof housings are necessary; anti-fouling surface treatments; and self-cleaning technology	[53,54]
Energy issue	Battery depletion and power autonomy	Low or no stable electricity and small energy budget	Use low-power microcontrollers; battery recycling	[14,16,33]
Economic challenge	High cost, maintenance, and replacement issues	Limited funding and a lack of affordable hardware	Alternative financing models (community cooperatives, public-private partnerships, and NGO-supported financing)	[29,30,33]
Human capacity	Skill gaps (in technical and maintenance issues)	Lack of training and exposure to AI, edge computing, and sensor networks	Upskilling of the workforce through training, partnerships with academic institutions, and local technological networks	[6]
Governance and data trust	Unclear data ownership and low community trust	Lack of transparency in data and AI models, and no community engagement	Co-design of participatory surveillance systems (community, governance, open algorithm, and explainable AI)	[18,20,21]

The success of edge AI systems has been built on the ability of sensors to deliver accurate and stable readings [18,26,31,55]. When installed in rivers, sensors typically suffer from drift, biofouling, and signal interference caused by temperature, dust, and deposition [53]. These issues contribute to false alarms and missed contamination events. In addition, predictions that are incorrect lead to unnecessary public health alarms and intervention measures, while false negatives pose a bigger risk for public health since the occurrences of contamination will go unnoticed. False-positive predictions can be dangerous, but edge AI is not a technology that guarantees there will not be any mistakes; it just helps cut down on decision-making delays through instant inference in local environments. In remote areas, manual calibration is problematic; therefore, it must either self-calibrate or use AI for the calibration process. Improvements in dynamic calibration algorithms, which have lower error rates than fixed algorithms, have been identified [66]. Nevertheless, the application of such algorithms in low-power microcontrollers remains a significant research gap.

Monitoring solutions in areas with low WASH resources, such as in African countries, to achieve high accuracy are necessary, as they must be affordable, robust, and autonomous. Evidence from previous studies has shown that edge AI systems combined with low-cost sensors provide the most practical approach to support real-time water quality monitoring and reduce dependence on cloud connectivity [14,16,26,40]. In addition, monitoring approaches that reduce privacy risks and increase community engagement should be recommended. System design should consider energy efficiency through decentralised solar charging and material chemistry for long life. In addition, lightweight tiny ML models generally perform better than computationally expensive deep learning methods in low-power and resource-constrained settings [44]. Sustainability is dependent on an autonomous system powered by solar energy, easy maintenance, and community ownership and operation with governance systems that create trust, accountability, and ensure long-term operation [20,21]. Hence, scale-appropriate water surveillance in underserved contexts is best facilitated through low-power, locally maintainable edge AI architectures integrated with low-cost sensing systems and participatory deployment [10].

Despite promising evidence from previous studies, the results supporting the implementation and deployment of edge AI in monitoring water quality are still limited. Numerous studies involving laboratory-based techniques are mostly conducted in urban areas rather than in rural or low-resource areas, with more studies reporting on accuracy prediction, cost, and sensor's efficacy or degradation [5,6,23,29,30,55]. These limitations hold back the overview of the current findings, highlighting the need for large-scale and long-term field studies in both rural and low-resource communities.

The introduction of edge AI technologies in low-resource communities requires a proper balance between the economic feasibility and sustainability of such technologies. The benefits that edge AI has when compared to those of cloud-based architectures include reduced communication bandwidth, reduced cloud computing and lower response latency, which also results in energy savings for applications where the connection to the internet is unreliable [45,52]. Moreover, the use of inexpensive embedded devices, such as ESP32, Arduino, Raspberry Pi, and other microcontrollers that support TinyML technologies, along with renewable energy, can be an economically sound solution to implement the monitoring of water quality [40]. Nevertheless, although edge AI has some obvious advantages in this context, most of the reviewed papers lack detailed information regarding economic factors such as expenses on hardware and software, energy consumption, maintenance, replacement of sensors, and life-cycle costs, making any comparison and technoeconomic analysis impossible.

10. Cybersecurity, Data Privacy, and Adversarial Attacks in Edge AI Systems

The distributed architecture of edge AI systems presents cybersecurity and privacy challenges on water quality monitoring that have not been adequately addressed in the literature. Unlike cloud systems, edge AI uses IoT sensors and edge devices connected through wireless networks, which results in increased attack surface and vulnerability to sensor spoofing, data tampering, DoS attacks, and adversarial machine learning when the modification of inputs causes incorrect predictions made by the AI algorithms [52]. These threats can lead to false alerts about the contamination of the water or to masking cases of pollution. Moreover, the transfer of environmental data through distributed networks entails risks to data confidentiality, integrity, and security, particularly when these technologies are used in water infrastructure [18]. New technologies, such as federated learning, end-to-end encryption, blockchain-based authentication, secure booting processes, and XAI (explainable artificial intelligence), are some of the techniques addressing these challenges. However, little research has been done on examining the robustness of AI-based water-quality monitoring systems against cyberattacks in operational environments, demonstrating the importance of designing secure and robust solutions to deploy such applications in resource-constrained settings.

11. Recommendation, Future Research Direction, and Roadmap

Despite the improvements made in smart water-quality monitoring, several technical infrastructure and governance challenges continue to limit the implementation of edge AI systems in rural settings. Based on the synthesised literature presented in this review, to overcome these challenges and promote the widespread deployment of edge AI technology and adoption of sustainable smart water-safety monitoring systems, we propose the following roadmap. Short-term future studies should focus on addressing fundamental barriers related to data availability, sensor readability, and field validation on a large scale to evaluate robustness under diverse environmental conditions, particularly in rural and low-resource settings. There is a need to promote the widespread deployment of edge AI technology; open-source edge platforms should be licensed freely and exhibit local adaptability. Since the current scarcity of labelled microbial contamination datasets remains the major obstacle to the deployment of these technologies, the development of open-access chemical and microbial water quality datasets should be prioritised to support training and benchmarking of machine learning algorithms.

In the medium term, research should transition from traditional monitoring systems towards intelligent and interconnected water-management platforms. Key priorities should include implementing a federated learning system to improve model accuracy without the need for data centralisation [67], thereby addressing privacy and connectivity challenges; utilising eco-friendly hybrid energy solutions (solar and microbial fuel cells) to maintain smooth operational continuity [68]; and fostering government–academia–private sector cross-sectoral collaboration to establish regional data infrastructure. The introduction of current technologies and the utilisation of interdisciplinary approaches enable the expansion, strengthening, and comprehensiveness of advanced AI frameworks, particularly in resource-constrained environments. In addition, central calibration techniques should also be developed to minimise maintenance requirements and improve long-term measurement accuracy. These advances would enhance system scalability while reducing dependence on technical expertise in remote communities. Future water-quality monitoring systems will become more intelligent and effective when networks of sensors integrate physical, chemical, and biological parameters into a single adaptive platform, enabling visual

representation of water distribution, predictive simulation, and autonomous proactive decision-making.

Long-term priorities should include the development of fully autonomous edge AI-driven water quality surveillance, which will ensure continuous monitoring, predictive analysis and adaptive responses. Such technologies can be nanomaterial-based and lab-on-a-chip biosensing, which can sense extremely small quantities of microplastics, drug contamination, and antibiotic resistance (AMR) genes in real time [54,58], and are necessary for water quality monitoring, thereby contributing to public health protection. There has been increased recognition of antimicrobial resistance (AMR) in freshwater, posing a threat to public health. Wastewater, surface water, and drinking water sources harbour such AMR genes, and the transmission pathways for resistance genes and antibiotic-resistant bacteria are not fully studied. Hence, future edge AI can incorporate molecular biosensors for the detection of AMR to support public health risk assessment. New self-healing and self-calibrating sensors using embedded AI algorithms and automatic drift compensation are necessary to reduce maintenance costs and improve the resilience of water infrastructure in vulnerable communities. Federated learning combined with AI will be essential because edge devices can cooperatively train AI models on local data without transmitting raw data, sharing only model parameters. This is a more privacy-friendly solution that reduces bandwidth consumption and performs better in disparate geographical locations [17].

An important direction for future research would be the way to address the existing technological barriers for implementing edge AI systems to monitor water quality in underserved communities and to facilitate their large-scale deployment. Although the current achievements in the field of AI, IoT and edge computing are very promising, there are still several crucial problems to solve. Firstly, standardized benchmarks and datasets need to be created to increase the comparability and reproducibility of machine learning models. Secondly, robust machine learning models capable of working under various conditions (sensor drift, missing data, seasonality and water quality change) must be developed. Thirdly, energy-efficient and lightweight AI algorithms such as TinyML must be further optimized for implementation in low-resource devices. Fourthly, the heterogeneity and interoperability of sensors, communication protocols, and cloud-edge architectures must be improved. Lastly, cybersecurity, uncertainty quantification, and XAI and standardized technoeconomic reports should be considered in future research studies. Further research is also needed for exploring the role of edge AI in tandem with digital twins, which would facilitate real-time simulation, prediction, and decision-making, along with integrating renewable energy sources including solar energy into edge nodes that provide sustainable autonomous water-quality monitoring capabilities in disadvantaged communities.

Energy autonomy is the most important limiting factor in water monitoring in rural areas [14,16,34]. Future systems should have hybrid renewable energy technologies, such as solar fuel cells, thermoelectric devices, and microorganisms, integrated into them to maintain an environmentally friendly process. Other studies have demonstrated energy harvesting edge nodes through mechanical vibration and biochemical energy from water biofilms that run without recharging a battery for a year [69,70]. The application of edge node technology will bring sustainability and reduce the environmental impact associated with battery disposal. It is necessary to create a platform that unifies sensors, AI models, edge devices, communication networks, and governance mechanisms and builds them into a scalable, autonomous water-safety architecture. The success in the implementation of this roadmap will require interdisciplinary collaboration among engineers, microbiologists, data scientists, governance experts, policymakers, and water utility professionals. Such coordinated efforts are essential to transform current evidence-based technology into a

practical, scalable, and sustainable solution for achieving safe water access in low-resource settings. The roadmap will directly support SDG 6 by enabling robust, affordable, and real-time water quality management in underserved communities.

12. Perspectives on Implications for Water Treatment and Water Quality Monitoring

The importance of edge AI in the water sector is expanding beyond water safety surveillance; it also has real implications in how we analyse water and how treatment is carried out. Classical monitoring methods tend to lean on periodic sampling, so contamination can be detected late because the warning comes only after the exposure has occurred [5,6,23]. On the other hand, real-time edge AI systems allow continuous checking of physicochemical and microbial contaminations, producing dense datasets. That makes it easier to assess how contamination evolves, and which environmental risk factors are actually driving it, rather than merely measuring contaminant levels. From a water-treatment perspective, incorporating edge AI into the workflow can support adaptive control strategies. During the prediction of turbidity, microbial contamination, chemicals, nutrient loading, and even emerging pollutants in near real time, treatment plants can adjust coagulant dosing, tune filtration behaviour, refine disinfection steps, and manage energy usage more carefully. Some recent work in advanced water treatment points to a growing interest in intelligent monitoring solutions that support automated operational decision-making [45,46]. Furthermore, edge AI holds substantial potential for anti-microbial resistance surveillance, early outbreak detection, and climate-resilient water management. By allowing localised decision-making with minimal reliance on cloud infrastructure, these technologies may provide a practical route to sustainable and equitable water management in low-resource settings. In the future, research should focus on integrating these technologies with treatment operations, risk assessment and management frameworks and public health surveillance programmes to maximise societal impact.

13. Conclusions

Edge AI and Internet of Things (IoT) sensing are transformative and environmentally sustainable technologies with significant potential for low-income water quality monitoring applications. From the reviewed evidence, it is clear that edge AI is among the most promising solutions for decentralized water quality monitoring in low-resource communities, as this solution allows for real-time data processing and decision-making with minimal communication needs. Nevertheless, the reviewed evidence suggests that there are very few case studies examining system reliability and sustainability in the field under different environmental and socioeconomic conditions, as the majority of existing evidence relates to laboratory experiments, simulations and pilots. Low-power microprocessors can run state-of-the-art AI algorithms in a spatially decentralised manner under real-world operating conditions without consuming excessive power. This decentralisation prevents the need for sample preservation and transportation and enables real-time operation. These technologies have shown promising performance in the early deployment of global waterborne disease outbreak predictions. Even though they have incredible potential, many aspects limit the adoption of edge AI monitoring systems. Some technical issues include sensor drift and biofouling, lack of energy autonomy, poor data quality, unavailable microbial training data, and few validation studies in African countries and other low-income regions. Moreover, socioeconomic aspects, such as high deployment costs, insufficient expertise, and a lack of governance frameworks regarding trust, ownership, and long-term maintenance, are crucial considerations. Future investigations should focus on advancing solid multimodal sensor platforms, adaptive and lightweight AI models

that are compatible with microcontrollers, and federated learning methods that facilitate model updating without the need for centralised data sharing. Deployment strategies led by communities, open-source edge frameworks, and administrations that facilitate such development will be necessary to guarantee fair deployment. The integration of edge AI with biosensors presents a promising approach for rapid microbial and chemical detection and outbreak prevention. The remaining challenges include generating microbial datasets for rural communities, conducting AMR monitoring and field validation, and developing practical edge AI systems for public health intervention. There is enough evidence of pilot-scale success, but long-term validation of the technology in field trials under different climatic and operational conditions needs to be done. Hence, although the results presented by existing research demonstrate the significant potential of edge AI for sustainable water quality monitoring, they also present a potentially fulfilling route to a water, sanitation, and hygiene (WASH) surveillance system that is both expandable and resilient, contributing directly to achieving Sustainable Development Goal 6 by providing better access to safe water via low-cost, real-time, and contextually suitable water-quality monitoring systems. However, performance evaluations are needed before the solution can be widely implemented.

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References

1. Angelakis, A.N.; Capodaglio, A.G.; Kumar, R.; Valipour, M.; Ahmed, A.T.; Baba, A.; Dercas, N. Water Supply Systems: Past, Present Challenges, and Future Sustainability Prospects. *Land* **2025**, *14*, 619.
2. Maryam, B.; Farooq, S.; Ali, A.; Gul, S.U.; Ullah, K.; Ullah, Z. Prevalence of waterborne diseases in district Karak, Khyber Pakhtunkhwa, Pakistan. *J. Med. Health Sci. Rev.* **2025**, *2*, 4580–4590. [CrossRef]
3. UNICEF; WHO. *Progress on Household Drinking Water, Sanitation and Hygiene 2000–2024: Special Focus on Gender*; World Health Organization: Geneva, Switzerland, 2025.
4. Abubakar, A.K.; Gillam, L.; Sastry, N. The Role of the Internet of Things (IoT) in Achieving the United Nations (UN) Sustainable Development Goals (SDGs)—A Systematic Review. *ACM Comput. Surv.* **2025**, *58*, 81. [CrossRef]
5. Thagafi, A.; Hassn, S.; Mutairi, A.; Aqeel, A.; Qassem Khalied, O.; Sbeay, A.; Ebrahim, N.; Sowailim, A.; Ismaile, S. Revolutionizing Healthcare: The Technological Transformation of Medical Laboratory Outcomes. *Int. J. Biol. Pharm. Sci.* **2022**, *8*, 1–8. [CrossRef]
6. Jahid, K.; Latif, R.; Saddik, A. AI-Driven Technologies for Water Quality Monitoring: A Comprehensive Review and Future Perspectives. In *2025 International Conference on Circuit, Systems and Communication (ICCSC)*; IEEE: New York, NY, USA, 2025; pp. 1–5.
7. VidhyaJanani, J.; Vigneshwaran, G.; Vikram, N.; Kandathil Radhakrishnan, D.; Saranya, R.; Manojkumar, R.; Deepa, D. Artificial Intelligence in Water Quality Monitoring for Sustainable Resource Management. *Int. J. Environ. Sci.* **2025**, *11*, 1528–1534. [CrossRef]
8. Kato, M.; Rodrigues, T.K.; Kato, N. Breakout local search solution to the offloading decision problem in a multi-access edge computing cloud-enabled network. *IEEE Trans. Emerg. Top. Comput.* **2025**, *13*, 1328–1338. [CrossRef]
9. Bhardwaj, A.; Dagar, V.; Khan, M.O.; Aggarwal, A.; Alvarado, R.; Kumar, M.; Proshad, R. Smart IoT and machine learning-based framework for water quality assessment and device component monitoring. *Environ. Sci. Pollut. Res.* **2022**, *29*, 46018–46036. [CrossRef] [PubMed]
10. Zhang, Y.; Feng, J. Towards a Smart and Sustainable Future with Edge Computing-Powered Internet of Things: Fundamentals, Applications, Challenges, and Future Research Directions. *J. Inst. Eng. Ser. B* **2025**, *106*, 785–804. [CrossRef]

11. Ogenyi, F.C.; Ugwu, C.N.; Ugwu, O.P.C. Securing the future: AI-driven cybersecurity in the age of autonomous IoT. *Front. Internet Things* **2025**, *4*, 1658273. [CrossRef]
12. Xue, X.; Dhumras, H.; Thakur, G.; Shukla, V. Integrating artificial intelligence and sustainable materials for smart eco innovation in production. *Sci. Rep.* **2025**, *15*, 36942. [CrossRef] [PubMed]
13. Gill, S.S.; Golec, M.; Hu, J.; Xu, M.; Du, J.; Wu, H.; Uhlig, S. Edge AI: A taxonomy, systematic review and future directions. *Clust. Comput.* **2025**, *28*, 18. [CrossRef]
14. Yadav, H.; Murugan, V.; Vijayakanthan Naik, K.J.; Mathurkar, P.; Urkude, G. Integrating Edge Computing And IoT For Real-Time Air And Water Quality Monitoring Systems. *Int. J. Environ. Sci.* **2025**, *11*, 1507–1511. [CrossRef]
15. Katende, R. Rethinking data-efficient artificial intelligence for low-resource settings. *Mach. Learn. Appl.* **2025**, *23*, 100796. [CrossRef]
16. Raj, P.; Akilandeswari, J.; Marimuthu, M. The edge AI paradigm: Technologies, platforms and use cases. In *Advances in Computers*; Elsevier: Amsterdam, The Netherlands, 2022; Volume 127, pp. 139–182.
17. Supriadi, C.; Wahyudi, W.; Priyadi, A.; Kim, J. Decentralized AI on The Edge: Implementing Federated Learning for Predictive Maintenance in Industrial IoT Systems. *J. Technol. Inform. Eng.* **2025**, *4*, 317–336. [CrossRef]
18. Korra, C.; Sadhana, A.V. Integrating IoT Sensors, Cloud AI, and Satellite Broadband for Enhanced ESG Governance in Smart Cities: A Tripartite Approach to Real-Time Environmental Monitoring. *Int. J. Innov. Sci. Res. Technol.* **2024**, *9*, 1378–1385. [CrossRef]
19. Huang, Y.P.; Khabusi, S.P. Artificial intelligence of things (AIoT) advances in aquaculture: A review. *Processes* **2025**, *13*, 73.
20. Khatide, N.N.; Laka, K.V.S.; Khauoe, T.N. Applications and Challenges of Network Technologies in IoT-Based Biological Water Monitoring Systems. *Res. Sq.* **2025**. [CrossRef] [PubMed]
21. Phulmante, U.; Sathe, U.; Sawant, V.; Sabale, S.R. Smart Water Distribution Monitoring System: A Review. *Int. J. Adv. Eng. Manag.* **2024**, *6*, 564–567. [CrossRef]
22. Mwashita, W. Recent Developments in Artificial Intelligence (AI) Sensors. In *Measurement, Automation, and Control in Artificial Intelligence and Machine Learning*; Springer: Cham, Switzerland, 2025; pp. 229–245.
23. Shende, A.D.; Tekade, S.A.; Deshmukh, A.A.; Tembhurkar, S.P.; Selvakumar, P. Water quality monitoring and control with AI. In *Smart Water Technology for Sustainable Management in Modern Cities*; IGI Global Scientific Publishing: Hershey, PA, USA, 2025; pp. 51–80.
24. Perrone, G.; Vecchio, M.; Del Ser, J.; Antonelli, F.; Kapoor, V. The Internet of things: A survey and outlook. In *Sensors in the Age of the Internet of Things: Technologies and Applications*; Institution of Engineering and Technology: Hertfordshire, UK, 2019; pp. 1–34. [CrossRef]
25. Patel, J.K. A Review of Artificial Intelligence Applications in Cloud Operations: Automation, Optimization, and Future Directions. *Int. J. Adv. Res. Sci. Commun. Technol.* **2025**, *5*, 489–499. [CrossRef]
26. Abdulkadhim, M.; Repas, S.R. SHEAB: A Novel Automated Benchmarking Framework for Edge AI. *Technologies* **2025**, *13*, 515. [CrossRef]
27. Mohapatra, S.; Sahoo, A.; Mohanty, S.; Singh, D. IoT-enabled ubiquitous healthcare system using predictive analytics. *Procedia Comput. Sci.* **2023**, *218*, 1581–1590. [CrossRef]
28. Pichel, N.; Hymnô de Souza, F.; Sabogal-Paz, L.P.; Shah, P.K.; Adhikari, N.; Pandey, S.; Shrestha, B.M.; Gaihre, S.; Pineda-Marulanda, D.A.; Hincapie, M.; et al. Field-testing solutions for drinking water quality monitoring in low- and middle-income regions and case studies from Latin American, African and Asian countries. *J. Environ. Chem. Eng.* **2023**, *11*, 111180. [CrossRef]
29. Yang, Z.; Barceló, D. Biosensors and New Analytical Methods for Wastewater-Based Epidemiology. *Trends Anal. Chem.* **2023**, *162*, 116961. [CrossRef]
30. Jain, P.; Pateria, N.; Anjum, G.; Tiwari, A.; Tiwari, A. Edge AI and On-Device Machine Learning for real-time processing. *Int. J. Innov. Res. Comput. Commun. Eng.* **2023**, *12*, 8137–8146. [CrossRef]
31. Sathio, A.A.; Singh, V.K.; Anwar, S.; Vavekanand, R. Real-Time Industrial Water Pollution Evaluation Using Edge–Cloud IoT Architecture and Multi-Parameter Sensing. *Non-Destr. Test.* **2025**, *3*, 21. [CrossRef]
32. Miller, M.; Kisiel, A.; Cembrowska-Lech, D.; Durlik, I.; Miller, T. IoT in Water Quality Monitoring—Are We Really Here? *Sensors* **2023**, *23*, 960. [PubMed]
33. Kshatri, D.; Parikh, P.; Joshi, K.D. Smart Water Flow Monitoring and Forecasting System using IoT and Machine Learning. *Int. J. Res. Appl. Sci. Eng. Technol.* **2025**, *13*, 862–873. [CrossRef]
34. Khurshid, H.; Mumtaz, R.; Alvi, N.; Haque, A.; Mumtaz, S.; Shafait, F.; Dengel, A. Bacterial prediction using Internet of Things (IoT) and machine learning. *Environ. Monit. Assess.* **2022**, *194*, 133. [CrossRef] [PubMed]
35. Tatiraju, T.; Dhineshkumar, K.; Mishra, H.; Sekar, C.P. Machine Learning-Enhanced Wireless Sensor Networks for Real-Time Environmental Monitoring. *Int. J. BIM Eng. Sci.* **2024**, *10*, 18–25. [CrossRef]
36. Jordan, P.; Cassidy, R. Perspectives on water quality monitoring approaches for behavioural change research. *Front. Water* **2022**, *4*, 917595. [CrossRef]

37. Fayiah, M.; Kandeh, B.; Izah, S.C.; Saccoh, S. Rural water management status, threats, and prospects: A case study of Sierra Leone. In *Water Resources Management for Rural Development*; Elsevier BV: Amsterdam, The Netherlands, 2024; pp. 263–274. [CrossRef]
38. Vaquet, V.; Artelt, A.; Brinkrolf, J.; Hammer, B. Taking care of our drinking water: Dealing with sensor faults in water distribution networks. In *International Conference on Artificial Neural Networks*; Springer Nature: Cham, Switzerland, 2022; pp. 682–693.
39. Bajaj, K.; Sharma, B.; Singh, R. Implementation analysis of IoT-based offloading frameworks on cloud/edge computing for sensor generated big data. *Complex Intell. Syst.* **2022**, *8*, 3641–3658. [CrossRef]
40. Nguyen, A.T.; Ahn, Y. *Edge AI for Smart Energy Systems: A Comprehensive Review*; IntechOpen: London, UK, 2025. [CrossRef]
41. Lane, K.; Fuller, M.; Dyment, T.; Gagnon, G. Co-development of a risk assessment tool for use in First Nations water supply systems: A key step to water safety plan implementation. *Int. J. Hyg. Environ. Health* **2022**, *240*, 113916. [CrossRef] [PubMed]
42. Murthy, N.S.; Ahamed, S. Water quality monitoring and measuring physicochemical parameters using wireless sensor networks. *Afr. J. Aquat. Sci.* **2023**, *48*, 366–373. [CrossRef]
43. Ayad, A.G.; El-Gayar, M.M.; Hikal, N.A.; Sakr, N.A. Efficient Real-Time Anomaly Detection in IoT Networks Using One-Class Autoencoder and Deep Neural Network. *Electronics* **2024**, *14*, 104. [CrossRef]
44. Marozva, M.; Rushambwa, M.; BukhelaniMusiiwa, P. Enhancing Water Quality Forecasting with Lstm and Attention-based Deep Learning: Toward Scalable, Long-term Monitoring of Surface Water Bodies. *IJSAT—Int. J. Sci. Technol.* **2025**, *16*, 1–12. [CrossRef]
45. Kumar, P.M.; Hong, C.S. Internet of things for secure surveillance for sewage wastewater treatment systems. *Environ. Res.* **2022**, *203*, 111899. [CrossRef] [PubMed]
46. Wang, Y.Q.; Wang, H.C.; Wang, W.Z.; Yang, H.L.; Chen, J.J.; Fan, Y.X.; Wang, A.J. Federated machine learning enables risk management and privacy protection in water quality. *Environ. Sci. Technol.* **2025**, *59*, 10310–10322. [CrossRef] [PubMed]
47. Jani, Y. AI and Machine Learning for Predictive Monitoring in IT Operations. *Int. J. Sci. Res.* **2023**, *12*, 2135–2140. [CrossRef]
48. Zhang, Q.; Gallard, J.; Wu, B.; Harwood, V.J.; Sadowsky, M.J.; Hamilton, K.A.; Ahmed, W. Synergy between quantitative microbial source tracking (qMST) and quantitative microbial risk assessment (QMRA): A review and prospectus. *Environ. Int.* **2019**, *130*, 104703. [CrossRef] [PubMed]
49. Miller, T.; Durlik, I.; Kostecka, E.; Kozlovska, P.; Łobodzińska, A.; Sokołowska, S.; Nowy, A. Integrating artificial intelligence agents with the internet of things for enhanced environmental monitoring: Applications in water quality and climate data. *Electronics* **2025**, *14*, 696.
50. Zhao, J. Water quality prediction based on High-Dimensional Dataset Integration Prediction Model. *Pak. J. Life Soc. Sci.* **2024**, *22*, 9611–9622. [CrossRef]
51. Jena, P.; Rahaman, S.M.; Mohapatra, P.K.D.; Barik, D.P.; Patra, D.S. Surface water quality assessment by Random Forest. *Water Pract. Technol.* **2022**, *18*, 201–214. [CrossRef]
52. Walshire, L.A.; Gonzalez, M.E.; Lillycrop, J.; Seamster, E.; Winters, K.E. Water resources infrastructure digital twins: Design, development, and future efforts. In *Geo-Congress*; American Society of Civil Engineers: Reston, VA, USA, 2023; pp. 400–408.
53. Silva, G.; Campos, D.F.; Brasil, J.A.T.; Tremblay, M.; Mendiondo, E.M.; Ghiglieno, F. Advances in Technological Research for Online and In Situ Water Quality Monitoring-A Review. *Sustainability* **2022**, *14*, 5059. [CrossRef]
54. Kashyap, R.; Chauhan, A.; Negi, A.; Chaudhary, G.R.; Sharma, R. Biosensors. In *Advanced Materials for Biomedical Applications: Development and Processing*; Springer Nature: Singapore, 2023; pp. 167–183.
55. Okpara, E.C.; Ajiboye, T.O.; Onwudiwe, D.C.; Wojuola, O.B. Optical and Electrochemical Techniques for Point-of-Care Water Quality Monitoring: A review. *Results Chem.* **2022**, *5*, 100710. [CrossRef]
56. Lvova, L.; Di Natale, C.; Paolesse, R. Chemical Sensors for Water Potability Assessment. In *Bottled and Packaged Water*; Woodhead Publishing: Sawston, CA, USA, 2019; pp. 177–208. [CrossRef]
57. World Health Organization. *Drinking Water: Key Facts*; WHO: Geneva, Switzerland, 2022.
58. Yin, W.; Hu, K.; Yu, B.; Zhang, T.; Mei, H.; Zhang, B.; Zou, Z.; Xia, L.; Gui, Y.; Yin, J.; et al. Fast and sensitive detection of viable Escherichia coli O157:H7 using a microwell-confined and propidium monoazide-assisted digital CRISPR microfluidic platform. *Lab Chip* **2024**, *24*, 4659–4668. [CrossRef] [PubMed]
59. Munawar, H.S.; Ullah, F.; Qayyum, S.; Khan, S.I.; Mojtahedi, M. UAVs in disaster management: Application of integrated aerial imagery and convolutional neural network for flood detection. *Sustainability* **2021**, *13*, 7547.
60. Wang, S.Y.; Lin, W.B.; Shu, Y.C. Design of machine learning prediction system based on the Internet of Things framework for monitoring fine PM concentrations. *Environments* **2021**, *8*, 99.
61. Li, W.; Awais, M.; Ru, W.; Shi, W.; Ajmal, M.; Uddin, S.; Liu, C. Review of sensor network-based irrigation systems using IoT and remote sensing. *Adv. Meteorol.* **2020**, *2020*, 8396164. [CrossRef]
62. Hering, J.G. Managing the 'Monitoring Imperative' in the Context of SDG Target 6.3 on Water Quality and Wastewater. *Sustainability* **2017**, *9*, 1572. [CrossRef]
63. Laki, T.; Asif, T.; Mirza, N.; Uzgoren, M. Secure Data Sharing in Decentralized Networks: Encryption Techniques, Access Control Mechanisms, and Data Integrity Verification. *Lond. J. Interdiscip. Sci.* **2025**, *4*, 25–37. [CrossRef]

64. Musa, S.S.; Zennaro, M.; Libsie, M.; Pietrosemoli, E. Convergence of information-centric networks and edge intelligence for IoV: Challenges and future directions. *Future Internet* **2022**, *14*, 192.
65. Frêne, C.; Astorga-Roine, A.; Gale, T.; Sotomayor, B.; Báez-Montenegro, A.; Boisier, J.P.; Reid, B.L. The Mirage of Drinking Water Security in Chilean Patagonia: A Socio-Ecological Perspective. *Sustainability* **2025**, *17*, 8519. [CrossRef]
66. Chen, T.; Li, S.; Qiao, Y.; Luo, X. A robust and efficient ensemble of diversified evolutionary computing algorithms for accurate robot calibration. *IEEE Trans. Instrum. Meas.* **2024**, *73*, 7501814. [CrossRef]
67. Zhang, C.; Xie, Y.; Bai, H.; Yu, B.; Li, W.; Gao, Y. A survey on federated learning. *Knowl.-Based Syst.* **2021**, *216*, 106775. [CrossRef]
68. Srivastava, R.K.; Boddula, R.; Pothu, R. Microbial fuel cells: Technologically advanced devices and approach for sustainable/renewable energy development. *Energy Convers. Manag.* **2022**, *13*, 100160. [CrossRef]
69. Liu, X.; Ueki, T.; Gao, H.; Woodard, T.L.; Nevin, K.P.; Fu, T.; Fu, S.; Sun, L.; Lovley, D.R.; Yao, J. Generating Electricity from Water Evaporation Through Microbial Biofilms. *bioRxiv* **2022**. [CrossRef]
70. Osorio de la Rosa, E.; Vázquez Castillo, J.; Carmona Campos, M.; Romeli Barbosa Pool, G.; Becerra Nuñez, G.; Castillo Atoche, A.; Ortegon Aguilar, J. Plant Microbial Fuel Cells−Based Energy Harvester System for Self-powered IoT Applications. *Sensors* **2019**, *19*, 1378. [CrossRef] [PubMed]

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