

Artificial Intelligence in Smart Water Management: Emerging Technologies, Applications, Challenges, and Future Directions

Pragadeeshwaran Kannan 

Centre for Applied Geology, the Gandhigram Rural Institute (Deemed to be University), Gandhigram, Dindigul, Tamil Nadu, India.

OPEN ACCESS

Article Citation:

Pragadeeshwaran Kannan, "Artificial Intelligence in Smart Water Management: Emerging Technologies, Applications, Challenges, and Future Directions", International Journal of Recent Trends in Multidisciplinary Research, July-August 2026, Vol 6(04), 374-380.



©2026 The Author(s). This is an open access article distributed under the terms of the [Creative Commons Attribution License](https://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and

reproduction in any medium, provided the original author and source are credited. Published by 5th Dimension Research Publication

Abstract: Artificial intelligence (AI) is rapidly transforming water management by enabling data-driven prediction, intelligent monitoring, optimization, and decision support across water-resource systems. This review critically examines the emerging applications of AI in smart water management, with particular emphasis on the transition from conventional monitoring and prediction toward integrated decision-making and autonomous system control. The review synthesizes recent developments in machine learning, deep learning, Internet of Things (IoT)-based systems, reinforcement learning, explainable artificial intelligence, and emerging agentic AI approaches applied to water resources, water-quality monitoring, groundwater management, hydrological forecasting, reservoir operation, wastewater treatment, water-demand prediction, and smart water infrastructure. The major benefits of AI include improved prediction accuracy, real-time monitoring, early detection of water-quality deterioration, optimization of operational processes, and enhanced decision support. However, widespread implementation remains constrained by data quality and availability, model interpretability, computational requirements, cybersecurity risks, infrastructure limitations, high implementation costs, and regulatory and governance challenges. Particular attention is given to the emerging transition from AI-assisted decision support toward autonomous water-system control, where AI models can increasingly connect sensing, prediction, decision-making, and physical actions. The review further identifies key research gaps related to trustworthy and explainable AI, integration of heterogeneous data sources, physics-informed machine learning, human-in-the-loop decision-making, and equitable deployment in resource-constrained water systems. Finally, a conceptual framework is proposed linking sensing, AI-based prediction, decision support, autonomous control, and continuous feedback, providing a pathway toward resilient, intelligent, and sustainable water management systems.

Key Words: Artificial Intelligence, Water management, Regional scarcity.

1. Introduction

Water is a fundamental component of environmental sustainability, economic development, public health, and ecosystem functioning. Increasing population, rapid urbanization, climate variability, water-quality deterioration, groundwater depletion, and aging water infrastructure have created substantial challenges for the sustainable management of water resources [1,2].

Artificial Intelligence in Smart Water Management: Emerging Technologies, Applications, Challenges, and Future Directions

Conventional water-management approaches often depend on periodic monitoring, empirical assessment, and expert-driven decision-making, which may be insufficient for systems characterized by high temporal variability, large data volumes, and rapidly changing environmental conditions. The increasing availability of sensors, remote sensing observations, Internet of Things (IoT) devices, geographic information systems (GIS), and high-frequency monitoring networks has consequently generated new opportunities for data-driven water management [3,4].

Artificial intelligence (AI) has emerged as an important technological approach for addressing these challenges because of its ability to identify complex nonlinear relationships, process large and heterogeneous datasets, generate predictions, and support operational decision-making. Machine learning (ML), deep learning (DL), artificial neural networks (ANNs), ensemble learning, reinforcement learning (RL), and other AI-based approaches have increasingly been applied to water-quality assessment, hydrological forecasting, groundwater management, water-demand prediction, reservoir operation, wastewater treatment, flood and drought prediction, and water-distribution systems [1,5]. Recent reviews demonstrate that AI applications now extend across a wide range of water-resources engineering problems, including streamflow prediction, water-quality assessment, flood mapping, drought analysis, groundwater management, reservoir scheduling, and urban water operations [1]. The development of smart water management is also being accelerated by the integration of AI with IoT, remote sensing, cloud computing, GIS, and advanced sensor technologies. Such integration enables water systems to move beyond conventional data collection toward continuous monitoring and predictive management. For example, AI models can process real-time sensor observations to identify abnormal conditions, predict changes in water quality or demand, detect potential infrastructure failures, and provide decision support for operational management [3,4]. The combination of IoT-based sensing and ML can facilitate real-time water-quality monitoring, early detection of contamination, and data-driven decision-making [3]. Consequently, the integration of sensing, prediction, and control is creating a transition from conventional monitoring systems toward intelligent water-management systems.

Despite these advances, the application of AI to water management remains associated with important scientific and practical limitations. The performance of AI models is strongly dependent on the quality, quantity, representativeness, and accessibility of training data. Differences in environmental conditions between training and application areas can reduce model transferability and generalization. In addition, the black-box characteristics of several advanced AI models can limit their interpretability and acceptance in applications where decisions may directly affect public health, environmental safety, and critical infrastructure [6,1]. Cybersecurity, computational requirements, implementation costs, aging infrastructure, limited technical expertise, and regulatory uncertainties further influence the practical deployment of AI-based systems [7,3].

Recent developments are also shifting attention from AI-based prediction toward intelligent decision-making and autonomous control. In conventional systems, sensors generate information that is subsequently interpreted by human operators before physical actions are implemented. In AI-enabled systems, predictive models can provide continuous decision support, while emerging approaches involving reinforcement learning, digital twins, explainable AI, and agentic AI have the potential to connect sensing, prediction, decision-making, and system control. However, increased autonomy also introduces new requirements for transparency, validation, human oversight, cybersecurity, accountability, and governance [6,1]. Therefore, the future development of smart water management requires not only more accurate AI models but also reliable and responsible frameworks for integrating AI with physical water systems.

Although numerous studies have investigated individual applications of AI in water management, the rapidly expanding literature remains fragmented across different water sectors, AI methodologies, and operational scales. Existing reviews have frequently focused on specific applications such as hydrological prediction, water-quality monitoring, groundwater forecasting, wastewater treatment, or individual machine-learning approaches [3,8,9]. For example, recent reviews have specifically examined groundwater-level forecasting using machine-learning models and AI-based water-consumption assessment, demonstrating the rapid expansion of AI applications within individual water-management domains [9,8]. A broader critical assessment is therefore required to connect the evolution of AI techniques with their applications across integrated water systems and to examine the transition from prediction and decision support toward autonomous water-system management.

Accordingly, this review critically examines the development and application of AI in smart water management, covering water resources, groundwater, water quality, hydrological systems, water supply, wastewater treatment, and smart infrastructure. Particular emphasis is placed on the capabilities and limitations of different AI techniques, the integration of AI with IoT, remote sensing, GIS, and other digital technologies, and the emerging transition from monitoring and prediction to decision support and autonomous control. The review also identifies major research gaps related to data quality, explainability, generalization, cybersecurity, governance, and human oversight, and proposes future research directions for developing reliable, transparent, resilient, and sustainable AI-enabled water-management systems.

2. Review Methodology

2.1 Literature Search Strategy

A structured literature search was conducted to identify recent scientific studies addressing the application of artificial intelligence (AI) in water management and water-resources engineering. The literature search focused primarily on peer-reviewed publications indexed in major scientific databases, including Scopus and Web of Science, with supplementary searches conducted using ScienceDirect and IEEE Xplore where appropriate. The search period covered publications from 2010 to 2026 to capture the development of conventional machine-learning approaches as well as recent advances in deep learning, explainable artificial intelligence, reinforcement learning, Internet of Things (IoT)-enabled systems, and emerging autonomous and agentic AI applications.

Artificial Intelligence in Smart Water Management: Emerging Technologies, Applications, Challenges, and Future Directions

The search strategy combined keywords related to artificial intelligence with terms representing major water-management domains. The principal search terms included “artificial intelligence”, “machine learning”, “deep learning”, “water management”, “water resources”, “water quality”, “groundwater”, “hydrology”, “wastewater”, “water supply”, “reservoir operation”, “flood prediction”, “drought prediction”, “water demand”, “IoT”, “remote sensing”, “smart water”, and “autonomous water management”. Boolean operators such as AND and OR were used to combine the keywords and identify relevant publications.

2.2 Inclusion and Exclusion Criteria

Studies were considered eligible when they met the following criteria: (i) the study was published in a peer-reviewed scientific journal; (ii) artificial intelligence, machine learning, deep learning, or a related computational intelligence technique was applied to a water-management or water-resources problem; (iii) the study reported a clear application, methodological development, evaluation, or critical assessment of AI-based approaches; and (iv) sufficient methodological information was available to identify the water-management application and AI technique. Review articles were additionally considered to identify major research trends, methodological developments, and research gaps.

Studies were excluded when they were unrelated to water management, did not involve an AI-based approach, consisted only of non-peer-reviewed material, lacked sufficient methodological information, or focused exclusively on general AI applications without a direct connection to water systems. Duplicate records identified across databases were removed before the screening process.

2.3 Screening and Classification of the Literature

The identified publications were screened in multiple stages. First, duplicate records were removed. Titles and abstracts were subsequently examined to determine their relevance to AI-enabled water management. Potentially relevant studies were then assessed based on their full text and classified according to their primary application, AI technique, data source, spatial or temporal scale, and principal research objective.

The selected literature was classified into the following major application categories: (i) water-quality monitoring and prediction, (ii) groundwater management, (iii) hydrological forecasting, (iv) flood and drought prediction, (v) reservoir and surface-water management, (vi) water-demand forecasting, (vii) drinking-water and distribution systems, (viii) wastewater treatment, (ix) smart water infrastructure, and (x) autonomous and intelligent water-system control.

AI methodologies were categorized into machine learning, ensemble learning, artificial neural networks, deep learning, convolutional neural networks, recurrent neural networks, long short-term memory networks, reinforcement learning, explainable AI, physics-informed machine learning, and emerging generative and agentic AI approaches. This classification enables comparison of the capabilities, limitations, and suitability of different AI approaches across diverse water-management applications.

2.4 Analytical Framework

The reviewed studies were analyzed according to five interconnected dimensions: AI methodology, water-management application, data source, decision-making function, and level of system autonomy. The AI methodology dimension describes the computational technique used for prediction, classification, optimization, or control. The application dimension identifies the specific water-management problem addressed. The data-source dimension considers conventional monitoring data, sensor observations, remote sensing, GIS-derived information, IoT observations, and other heterogeneous datasets.

The decision-making dimension distinguishes between descriptive monitoring, predictive modelling, decision support, optimization, and automated control. The level-of-autonomy dimension further differentiates conventional human-operated systems from AI-assisted systems and emerging autonomous systems. This framework provides the basis for evaluating the transition from data collection and prediction toward integrated decision-making and autonomous water-system management.

2.5 Evaluation of AI Applications

The performance and practical relevance of AI applications were assessed using commonly reported indicators, including prediction accuracy, coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), classification accuracy, computational efficiency, interpretability, robustness, and transferability. Where appropriate, attention was also given to the availability and quality of training data, model validation procedures, uncertainty assessment, and the practical feasibility of implementation.

Particular emphasis was placed on limitations that may affect the transfer of AI models from experimental or site-specific studies to operational water-management systems. These limitations include data scarcity, inconsistent monitoring, model overfitting, limited interpretability, inadequate external validation, computational requirements, cybersecurity risks, infrastructure constraints, and the absence of standardized regulatory frameworks.

2.6 Research Gap Identification

Finally, the literature was critically examined to identify areas where existing research remains insufficient. Particular attention was given to the integration of heterogeneous data sources, explainable and trustworthy AI, physics-informed modelling, transferability between geographic regions, human–AI collaboration, cybersecurity, uncertainty quantification, and autonomous decision-making. The identified gaps were subsequently used to develop future research directions and a conceptual

Artificial Intelligence in Smart Water Management: Emerging Technologies, Applications, Challenges, and Future Directions

framework for the transition from conventional water monitoring toward intelligent, resilient, and increasingly autonomous water-management systems.

3. Why Water, Why Now

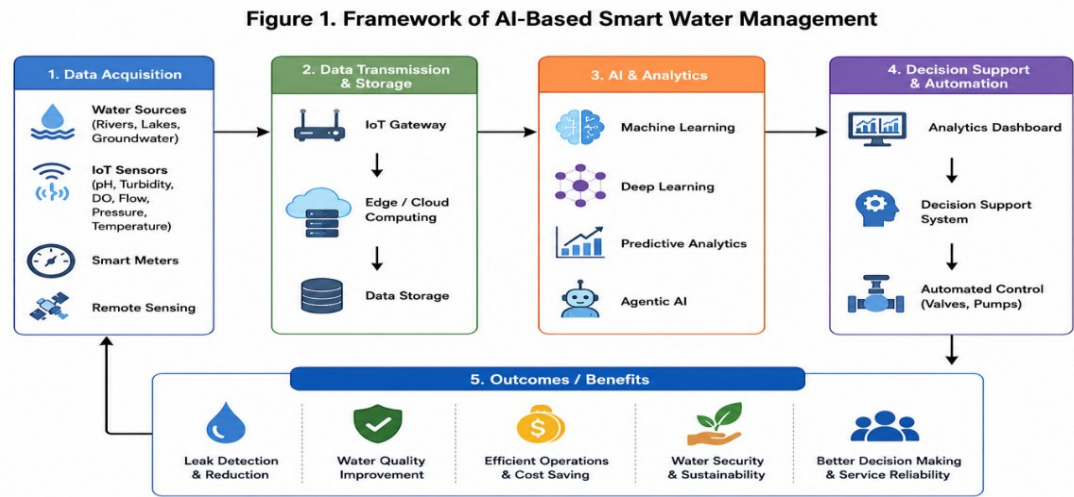
Several structural pressures are pushing water technology to the front of the agenda:

- **Regional scarcity and urbanization.** In the Asia-Pacific region alone, roughly 60% of the world’s population lives with access to only about 36% of global freshwater resources, and roughly 200 million people move into cities every decade, straining reservoirs, canals, and urban water systems.
- **Climate volatility.** The same demographic pressures are compounded by climate change, which is driving more severe flooding, longer droughts, and faster eutrophication of freshwater bodies [1].
- **Aging infrastructure and tightening regulation.** Utilities are contending with harmful algal blooms, PFAS regulation, climate volatility, and aging infrastructure at the same time, and regulators increasingly expect utilities to demonstrate data-driven management of their water systems [1,2].
- **Rising expectations from insurers and tenants.** Beyond utilities, commercial building owners face growing pressure to modernize: insurers, lenders, and tenants increasingly expect built-in water intelligence, comparable to fire protection or energy metering, and buildings without it are viewed as higher risk, harder to insure, and less aligned with ESG standards.
- **A genuinely enormous funding gap.** Even after years of federal investment, the EPA estimates \$625 billion in drinking water infrastructure needs over the next 20 years, a figure that dwarfs current funding commitments and creates sustained pressure to do more with the same physical assets — which is precisely where AI-driven efficiency gains are most attractive.

3. From Monitoring to Autonomous Action

AI Technique	Application	Advantages	Limitations
Machine Learning	Water quality prediction	High accuracy	Requires quality data
Deep Learning	Image analysis, contamination detection	Learns complex patterns	Large datasets required
Random Forest	Water quality classification	Robust and interpretable	Computational cost
Artificial Neural Networks	Demand forecasting	Nonlinear modeling	Black-box behavior
Reinforcement Learning	Reservoir operation	Adaptive optimization	High computational complexity
Agentic AI	Autonomous system control	Real-time decision-making	Governance and safety concerns

Table.1 Artificial Intelligence Techniques Used in Smart Water Management



The most significant technical advancement is the shift from passive monitoring to active response. Traditionally, divisions existed within water systems between sensing and decision-making [1]. This meant that sensors gathered data, humans inspected the reports and made decisions, and separate teams were subsequently sent to resolve the problems. This process is being condensed. AI platforms are transforming conventional plumbing infrastructure into intelligent systems capable of real-time monitoring, diagnosis, and autonomous response. They offer an active response which consists of the ability to monitor, shut off and diagnose, in real time [7]. The same logic is applied from a utility perspective to reservoirs and source waters.

Artificial Intelligence in Smart Water Management: Emerging Technologies, Applications, Challenges, and Future Directions

Businesses are investing in IoT sensors that are continuously monitored and allow for predictive models to respond to water quality actively before it declines [5,3].

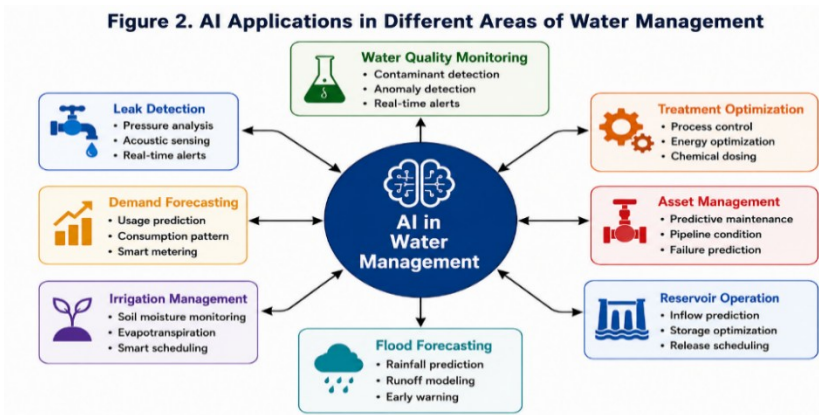
This shift is being called agentic by many of the larger water technology suppliers. Among other things, it shows the movement of agentic AI that has the ability to move from mere monitoring to performing actions like flow control, in the case of water AI, to turning valves and shutting them in the case of a detection of a leak. The overall framework is shown in Fig. 1 and Table 1.

4. Treatment and Supply Innovation

Along with smart sensing, the physical treatment side of this business is advancing quickly as well [10]. The latest study on the water treatment industry reveals the following key trends: desalination brings fresh water to places where it is scarce, modular systems provide more flexibility, and environmentally-friendly bio-based treatment along with nanofiltration are becoming increasingly popular. On the monitoring side, startups are increasingly using remote sensing, IoT devices, and machine learning to enable continuous, real-time detection of contaminants rather than periodic manual testing [3,4].

A notably vigorous subdomain is that of methods for eliminating PFAS [11]. In addition to merely filtering “forever chemicals” from water — a process that usually results in their concentration in a waste stream requiring separate disposal — the cutting edge now involves technologies that completely decompose these compounds. Regulators have emphasized the increasing array of deployable systems, and one water technology provider detailed the use of reverse-flow reverse osmosis to minimize the leftover, highly concentrated brine usually linked to conventional reverse osmosis treatment — indicating that treatment innovation is now focusing on the byproducts of previous treatment methods, rather than solely the original contaminant.

Water reuse is undergoing a reframing process as well. Utilities facing unstable surface water supplies are increasingly turning to reuse to reduce dependence on those sources rather than reserving it only for emergencies or arid regions, making what was once treated as a last resort a standard planning practice. The major AI application areas are shown in Fig. 2 and Table 2.



Study	AI Method	Water Application	Major Finding
Sit et al. (2020)	Deep Learning	Hydrology	Improved prediction accuracy
Essamlali et al. (2024)	Machine Learning	Water Quality Monitoring	Real-time monitoring
Jayaraman et al. (2024)	IoT + ML	Water Quality	Automated detection
Nagpal et al. (2024)	AI Optimization	Wastewater Treatment	Better treatment efficiency
Rashid et al. (2026)	AI Review	Water Resources	Emerging AI applications

Table 2. Recent AI Applications in Water Management

5. The Regulatory and Funding Backdrop

Water technology adoption in 2026 cannot be separated from an unusually active regulatory and funding environment in the United States, which is shaping investment decisions well beyond U.S. borders.

PFAS rulemaking is in flux, but funding continues [11]. In May 2026, the EPA proposed two significant rule changes: one upholds the national drinking water standard for PFOA and PFOS while giving utilities an option to request up to two additional years, until 2031, to reach compliance, and another would roll back drinking water regulations for several other PFAS compounds, including GenX and a combined hazard index. Even as the rules themselves are debated, funding has kept flowing: the agency has continued to highlight nearly \$1 billion in new funding to states specifically to address PFAS in drinking water alongside innovative treatment and destruction technologies. Officials have been explicit that a rules review is not automatically a weakening of standards — EPA has stated that future standards could ultimately become more stringent if the scientific

Artificial Intelligence in Smart Water Management: Emerging Technologies, Applications, Challenges, and Future Directions

evidence supports tougher limits, and part of the stated goal of extending compliance timelines is to ensure smaller communities are not left behind as national PFAS regulations expand.

Although the scale of the federal investment is unprecedented, the funding is not permanent. The Infrastructure Investment and Jobs Act set aside an historic \$55 billion for federal investment in water infrastructure, with a record \$11.7 billion for the Drinking Water State Revolving Fund, thanks to the IIJA. However, there is no assurance that funding will be provided at the same level again. During budget reconciliation in late 2025, approximately \$2.3 billion in unobligated IIJA water funds were rescinded. The IIJA water provisions are scheduled to end in September 2026, and at the time of this writing, Congress has not yet voted to continue them for fiscal year 2027. This poses a serious risk for planning. Infrastructure investment models that comply with the IIJA are underestimating the risk that IIJA will not be renewed. However, the need for hundreds of billions of dollars of new infrastructure will not change, regardless of funding decisions made by Congress.

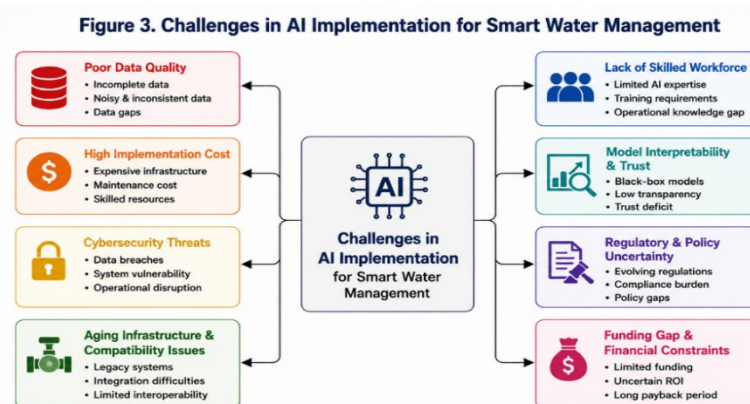
There are multiple, concurrent, and rapidly changing regulatory requirements for the same utilities. For example, sector analysts have noted that the 2024 PFAS drinking water rule, the 2024 Lead and Copper Rule Improvements, and the 2024 cybersecurity compliance mandates are rapidly converging, which creates three simultaneous capital expenditure demands for the same community water systems. This forces the same municipal utility to be funding the removal of lead service lines, the installation of PFAS treatment systems, and the fortification of operational technology systems against cyber intrusions and attacks. This is forcing many utilities to consider automation.

Consolidation becomes the major financial reaction. Instead of individual upgrading, smaller water systems are acquiring because of the burden effect. It is forecasted that by 2026 there will be more consolidation of water utilities because small private entities will be buying out small water systems all over the country. Even larger companies will get involved. The private equity understands that. Water utilities and wastewater utilities have been perceived as a long-term investment option for many years because of the hundreds of billions of dollars infrastructure gap.

6. Risks and Open Questions

Putting more autonomy into water infrastructure — against this financial and regulatory backdrop — raises a distinct set of concerns compared with agentic AI in general business software:

1. The impact of making the mistake is far more than the effect that comes about through the informational context [1]. While the chatbot may make mistakes but will only cause the disruption of the workflow process, the mistake made by an agent in misreading contamination signals or shutting down will be an interruption to the actual physical supply.
2. The aspect of auditability becomes increasingly important here [6]. As water is critical for people's health and regulated by laws, the systems based on artificial intelligence should not only function correctly but also be transparent and auditable — the thing which vendor of utility solutions already recognizes in their guidelines for 2026.
3. Funding is uncertain, which influences decisions regarding investments into automation. As there is a multibillion program of federal support, subject to rescission and without reauthorization settled yet, the utilities considering long-term investments into infrastructure have uncertainty whether the capital will be available to support such systems.
4. The deployment of automation is dependent upon infrastructure and regulatory burden [2]. The smart monitoring and automated solutions are easily deployed in the new buildings and large well-funded utilities [7]. However, there are disadvantaged utilities and communities which regulators fear could be left behind and which would still have to rely on conventional infrastructure because of financial and technical constraints
5. Consolidation changes who controls the automation. As private equity and larger utilities acquire smaller water systems, decisions about which AI platforms to deploy, and how much autonomy to grant them, increasingly sit with financial owners rather than local public authorities — raising governance questions distinct from the technology itself.
6. Byproduct management is becoming its own problem [2]. As destruction technologies mature, treatment is starting to target the concentrated waste streams left behind by earlier filtration methods, not just the original contaminants — a reminder that solving one part of the water problem can simply relocate it rather than eliminate it. The challenges is shown in Fig.3 and Table.3.



Challenge	Impact
Poor data quality	Reduces prediction accuracy
High implementation cost	Limits adoption
Cybersecurity threats	Infrastructure vulnerability
Explainability issues	Difficult regulatory approval
Funding uncertainty	Delayed deployment
Limited technical expertise	Slower implementation
Aging infrastructure	Integration challenges

Table 3. Challenges of AI Implementation in Water Management

7. Conclusion

The water management of 2026 demonstrates, in practical and tangible terms, the same transformation that is underway in the wider field of technology — namely, from information-gathering AI to decision-making AI. The reservoirs, treatment plants, and household pipes themselves are developing into parts of a continuous sense-decision-action process, rather than a regular monitoring and reporting system. All of this takes place in the context of great turbulence in regulation and finance — the era of massive government investment made possible by historic levels of funding uncertainty, regulations on PFAS being both tightened and rolled back, and the era of consolidation, changing ownership of utilities.

Given the increasing pressure caused by climate and infrastructure demands, whether or not the sector can combine autonomy with accountability and extend the benefits of infrastructure driven by AI to utilities that can afford it will probably determine which cities and utilities make it through the transformation successfully.

References

1. Rashid, M., Saeed, A., Khalid, M., Murtaza, A., & Saleem, M. W. (2026). The Transformative Role of Artificial Intelligence in Water Resources Engineering: A Comprehensive Review. *Environmental Modelling & Software*, 106857.
2. Zou, S., Ju, H., & Zhang, J. (2025). Water quality management in the age of AI: Applications, challenges, and prospects. *Water*, 17(11), 1641.
3. Essamlali, I., Nhaila, H., & El Khaili, M. (2024). Advances in machine learning and IoT for water quality monitoring: A comprehensive review. *Heliyon*, 10(6).
4. Jayaraman, P., Nagarajan, K. K., Partheeban, P., & Krishnamurthy, V. (2024). Critical review on water quality analysis using IoT and machine learning models. *International Journal of Information Management Data Insights*, 4(1), 100210.
5. Sit, M., Demiray, B. Z., Xiang, Z., Ewing, G. J., Sermet, Y., & Demir, I. (2020). A comprehensive review of deep learning applications in hydrology and water resources. *Water Science and Technology*, 82(12), 2635–2670.
6. Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., & Benjamins, R. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, 58, 82–115.
7. Alshami, A., Ali, E., Elsayed, M., Eltoukhy, A. E. E., & Zayed, T. (2024). IoT innovations in sustainable water and wastewater management and water quality monitoring: a comprehensive review of advancements, implications, and future directions. *Ieee Access*, 12, 58427–58453.
8. Nagpal, M., Siddique, M. A., Sharma, K., Sharma, N., & Mittal, A. (2024). Optimizing wastewater treatment through artificial intelligence: recent advances and future prospects. *Water Science & Technology*, 90(3), 731–757.
9. Ross, I., McDonough, J., Miles, J., Storch, P., Thelakkat Kochunarayanan, P., Kalve, E., Hurst, J., S. Dasgupta, S., & Burdick, J. (2018). A review of emerging technologies for remediation of PFASs. *Remediation Journal*, 28(2), 101–126.