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ADVANCEMENTS IN MONITORING, CONTROL, AND AUTOMATION TECHNOLOGIES FOR INTEGRATED SYSTEMS IN INDUSTRIAL EFFLUENT TREATMENT: A REVIEW

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Abstract
Effluent treatment in industries is of utmost importance in maintaining water quality, ecosystems, and public health. However, there exist challenges with respect to the response of traditional effluent treatment systems to effluent variations as well as high energy and chemical requirements. This paper presents recent developments in the field of monitoring, control, and automation techniques in integrated industrial effluent treatment systems with special consideration of IoT-based monitoring, artificial intelligence (AI), machine learning (ML), model predictive control (MPC), adaptive control, PLC/SCADA, and robotics. A systematic literature review was conducted based on PRISMA criteria for papers published between 2018 and 2026. This synthesis shows that IoT sensors provide continuous monitoring of the quality of water, while AI/ML algorithms can be applied for predicting, detecting anomalies, and optimizing processes. MPC and adaptive controls allow increasing responsiveness to changes in process conditions, while PLC/SCADA serves as the basis for the operational infrastructure for automated control and monitoring. Robotics is used in certain applications such as sampling, cleaning, inspection, sludge handling, and dosing chemicals. Integrating all these technologies will allow increasing the number of monitoring times, responsiveness of control, data consolidation, resource management, and efficiency of operations. Nevertheless, the evidence base is still heterogeneous with many studies relying on single location or study under controlled conditions, thus making generalizations difficult. Important obstacles are related to the implementation cost, sensor reliability, cybersecurity, lack of specialists, adjustment to regulations, and interoperability. The evidence supports progressive, human-supervised automation and increasingly data-driven integrated treatment systems rather than immediate full autonomy.

Keywords
Industrial Effluent Treatment, Wastewater, Artificial Intelligence, Automation, Model Predictive Control, Robotics.

1. INTRODUCTION

The treatment of industrial effluent is a core element of environmental management because of its direct effects on ecosystem health, human health, and water quality [1], [2]. Figure 1 shows how diverse industrial activities contribute distinct types of contaminants to wastewater streams. Unlike domestic wastewater, industrial effluent has a far more complex chemical composition, elevated pollutant concentrations, and substantial variability in flow and characteristics [3]. Industrial wastewater contains chemicals, heavy metals, and organic debris [4]; its uncontrolled release into the environment pollutes water bodies, depletes aquatic populations, and endangers human health [5]. Effective treatment is therefore essential to environmental protection [6]. However, several factors continue to limit the efficacy and efficiency of conventional industrial wastewater treatment. Standard physical, chemical, and biological treatment steps often struggle with the complex and variable nature of industrial wastewater [7], consume substantial energy and chemicals, and do not always remove pollutants to the required extent [8]. Conventional management also depends heavily on manual control and monitoring, which delays problem resolution [3] and complicates timely responses to changes in effluent composition and flow because adaptive control and real-time information are largely absent [7].

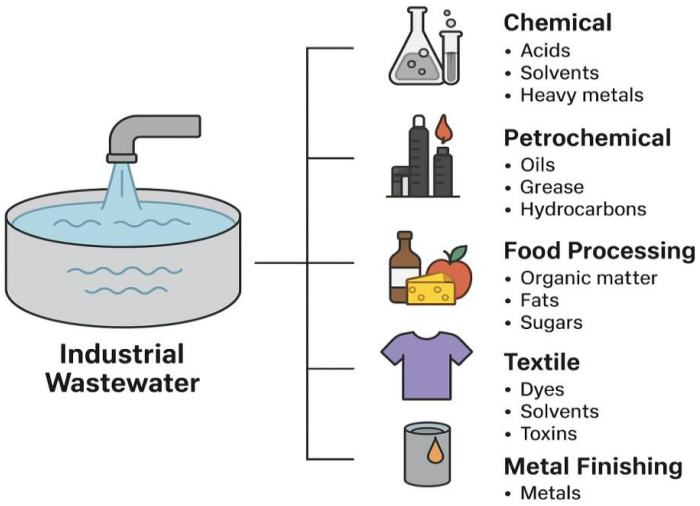


Fig. 1. Industrial water types and contaminants

Automation, control, and monitoring systems for industrial wastewater treatment have advanced considerably over the past decade [9]. IoT sensors now allow continuous, real-time tracking of key water-quality indicators, generating data that supports predictive maintenance and process improvement [10]. Model predictive control (MPC) and adaptive control provide more precise and flexible process management than fixed-rule strategies [11], while AI and machine learning (ML) enable the processing of large volumes of sensor data to optimize treatment in response to changing effluent properties [12]. Supervisory control and data acquisition (SCADA) and programmable logic controller (PLC) systems further improve the efficiency and sustainability of treatment operations [13].

Existing reviews in this domain tend to be technology-specific: several focus narrowly on IoT-based water-quality monitoring [2], on control-theoretic approaches to wastewater treatment [3], or on AI/ML applications in isolation [9], [46]. What is comparatively underexplored is a cross-cutting synthesis that (i) treats monitoring, control, and automation as an integrated system rather than as separate technology tracks, (ii) quantitatively compares the reported performance, cost, and reliability of competing approaches rather than describing them in parallel, and (iii) applies an explicit, auditable selection methodology to the underlying evidence base. This paper synthesizes the comparative evidence across monitoring, control, automation, and integration studies, evaluates the strength and limitations of that evidence, and situates the discussion within the most recent developments in the field,

The contributions of this paper are as follows:

i. Synthesis and comparison of monitoring, control, and automation technologies for industrial effluent treatment.

ii. A systematic, PRISMA-informed comparative study of traditional and intelligent wastewater treatment systems.

iii. Identification of the principal barriers to large-scale adoption of intelligent wastewater treatment systems, together with an outlook on recent and emerging trends.

2. REVIEW METHODOLOGY

This review followed a four-stage methodology, adapted from the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, to ensure a transparent and reproducible selection process: (1) literature identification, (2) screening and eligibility assessment, (3) quality evaluation, and (4) synthesis of findings. Figure 2 summarizes this process and the number of records retained at each stage.

2.1 Literature Identification

The first phase involved an extensive literature search of peer-reviewed and scientific databases, namely Scopus, Web of Science, SpringerLink, ScienceDirect, IEEE Xplore, and Google Scholar. These databases were selected for their comprehensive coverage of environmental engineering, computer science, industrial automation, and environmental monitoring research. The search covered publications from 2018 to 2026. Search queries combined specific keywords with Boolean operators; the main search string used was: “industrial wastewater” OR “industrial effluent treatment” AND “monitoring” OR “IoT sensors” OR “automation” OR “SCADA” OR “PLC” OR “artificial intelligence” OR “machine learning” OR “model predictive control” OR “predictive maintenance” OR “robotics.” This query captured articles relevant to monitoring technologies, control techniques, automation, and integrated systems.

2.2 Screening and Eligibility Criteria

The initial search returned 190 records, comprising journal articles, technical reports, and conference proceedings. These were screened against explicit inclusion and exclusion criteria. Inclusion criteria were:

1. Studies focusing on industrial wastewater or effluent treatment.
2. Research examining monitoring, control, automation, AI, or IoT-based systems.
3. Peer-reviewed journal articles and reputable conference proceedings.
4. Publications presenting empirical data, case studies, models, or comprehensive reviews of relevant technologies.

Records were excluded if they met any of the following conditions:

1. Focused solely on municipal wastewater without industrial relevance.
2. Lacked methodological clarity or sufficient technical detail.
3. Were not peer-reviewed.
4. Were not written in English or not available in full-text form.

Applying these criteria narrowed the pool from 190 to 130 studies retained for quality assessment (Fig. 2).

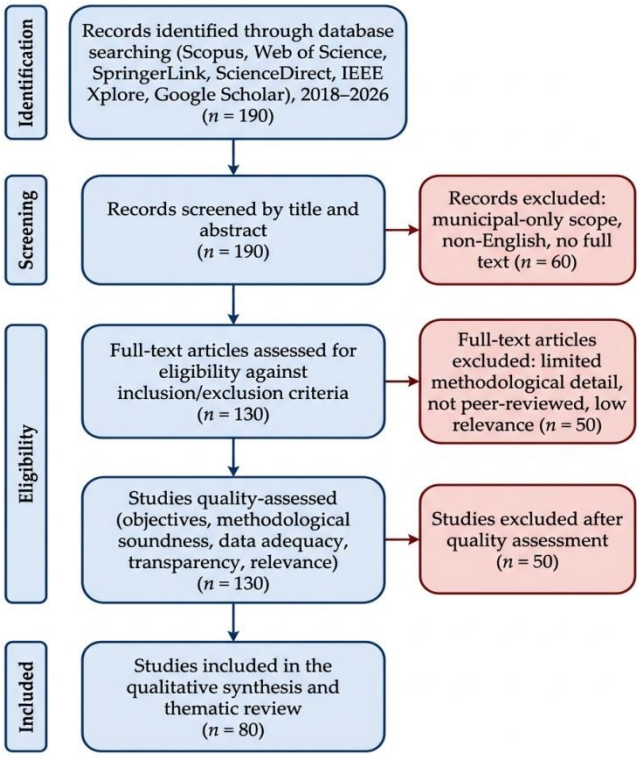


Fig. 2. PRISMA-style flow diagram of the literature identification, screening, eligibility, and inclusion process

2.3 Quality Assessment

The 130 shortlisted articles, spanning publication years 2018 to 2026, underwent a further evaluation of scientific validity, methodological soundness, and reliability. Each article was assessed against the following criteria:

i. Clarity of research objectives.
ii. Methodological soundness and robustness.
iii. Adequacy of data collection or experimental design.
iv. Transparency in the description of monitoring and control techniques.
v. Relevance of findings to industrial wastewater treatment.
vi. Quality and completeness of qualitative or quantitative analysis.

This assessment ensured that only credible, methodologically sound research informed the synthesis. Of the 130 articles assessed, 80 met the quality threshold and were included in the review (Fig. 2). These 80 articles, drawn from the 2018-2026 window, collectively form the evidence base for the synthesis of IoT-based monitoring systems, process control, AI/ML algorithms, robotics, automation, and integrated architectures.

2.4 Data Extraction and Synthesis

The 80 included articles were reviewed in full, and data were extracted according to a standardized framework covering the technology tested, application area, pollutant characteristics, system architecture, performance indicators, environmental impact, and limitations reported by the authors. Extracted data were

organized into five thematic domains corresponding to the structure of this review: monitoring technologies, control technologies, automation technologies, integration methods, and outstanding challenges.

2.5 Methodological Limitations

Despite the systematic approach, several limitations apply to this review. Heterogeneity in experimental set-ups, inconsistent reporting standards, and diverse research designs across the included studies precluded a formal quantitative meta-analysis. Blockchain-based monitoring systems and digital twins were also underrepresented in the available literature at the time of the search, reflecting their comparatively recent adoption in this domain. Similarly, restricting the search to English-language, full-text, peer-reviewed sources may have excluded relevant regional case studies.

3. MONITORING TECHNOLOGIES

Monitoring of changing conditions in the treatment plant is essential to the success of industrial wastewater treatment [9]. Conventional approaches rely on manual sampling and laboratory analysis, which cannot keep pace with the dynamic characteristics of industrial wastewater [14]. Advanced approaches involving automated systems, real-time data analysis, and the Internet of Things (IoT) have emerged to address this gap and have generally resulted in more efficient plant management [15].

3.1 IoT-Based Monitoring

IoT has enabled the deployment of networked sensors throughout the treatment plant [16], [17]; Table 1 summarizes the water-quality parameters commonly monitored by IoT sensors. Indicators such as pH, temperature, turbidity, chemical oxygen demand (COD), and biological oxygen demand (BOD) are continuously measured by IoT sensors. Unlike traditional monitoring, IoT systems allow operators to access real-time data and control the treatment process remotely [18]. Continuous monitoring supports timely identification and management of problems as they emerge. IoT sensor data are transmitted to centralized systems and displayed through dashboards for processing and analysis [19], helping operators identify where adjustments are needed. Coupling IoT-based monitoring with AI and ML can further improve prediction and process optimization [20]. Several studies point to the importance of IoT monitoring for early problem detection in industrial effluent systems [21]. Interval-based sampling is not always able to capture rapid changes in wastewater parameters, which can delay corrective action and increase remediation costs [22]. Continuous IoT data streams make problem detection faster [23], allowing staff to act in advance of unexpected changes such as a sudden rise in COD or an abrupt pH shift [24].

Table 1. Water-quality parameters monitored by IoT sensors

Parameter	Description	Importance	Typical IoT sensor type	Refs.
pH	Measures the acidity or alkalinity of the water.	Critical for chemical dosing and maintaining optimal conditions for biological treatment.	pH sensors (glass electrode, solid-state)	[25], [26]
Temperature	Indicates the thermal condition of the effluent.	Affects reaction rates and biological process performance.	Thermocouples, resistance temperature detectors (RTDs)	[27], [28]
Dissolved oxygen (DO)	Measures the oxygen available for biological treatment.	Essential for aerobic processes and receiving-water ecosystem health.	Optical DO sensors, electrochemical DO sensors	[29], [30]
Turbidity	Measures water clarity by detecting suspended particles.	Indicates solids loading affecting filtration and sedimentation.	Nephelometric turbidity sensors	[31], [32]
Chemical oxygen demand (COD)	Measures the total oxygen required to oxidize organic and inorganic matter.	Indicates overall organic load and treatment effectiveness.	Optical sensors, UV absorbance sensors	[33], [34]
Biological oxygen demand (BOD)	Measures the oxygen required by microorganisms to decompose organic matter.	Assesses biological treatment effectiveness and effluent quality.	Respirometric sensors, optical DO sensors	[35]

Parameter	Description	Importance	Typical IoT sensor type	Refs.
Total dissolved solids (TDS)	Indicates the concentration of dissolved substances in water.	Important for monitoring salinity and scaling risk.	Conductivity sensors, optical sensors	[36], [37]
Heavy metals (e.g., Pb, Hg)	Detects toxic metals present in the effluent.	Critical for regulatory compliance and preventing toxic pollution.	Electrochemical sensors, optical sensors	[38], [39]

3.2 Critical Synthesis and Limitations

Across the reviewed studies, optical and electrochemical sensing methods are consistently reported as offering the best combination of response time and measurement resolution for parameters such as DO, COD, and heavy metals, but at a materially higher unit cost and calibration burden than simpler conductivity- or thermocouple-based sensors [25]-[39]. This trade-off means the choice of sensor type is rarely purely technical: reported deployments favor lower-cost sensors (pH, temperature, conductivity) for continuous, plant-wide coverage, reserving optical and electrochemical sensors for critical control points. A recurring limitation across the IoT-monitoring literature is that reported accuracy and reliability figures are typically obtained under controlled or short-duration trial conditions; comparatively few studies report long-term sensor drift, fouling, or maintenance costs under continuous industrial operation, which limits confidence in claims of "continuous" real-time monitoring at scale.

4. OPTIMIZATION OF TREATMENT PROCESSES

Real-time data from monitoring systems is a key input to treatment-process optimization [40]. Continuous monitoring of variables such as temperature, pollutant concentration, and flow rate [18] enables adjustment of aeration rates, chemical dosages, and other process parameters, helping treatment goals to be met with lower resource consumption [41]. IoT monitoring systems can also reveal relationships in the data that are difficult to identify manually [42], supporting process prediction, modification recommendations, and control automation [43]. Some studies also report that machine learning models trained on historical and real-time data can help anticipate maintenance requirements [43].

IoT platforms are considered particularly powerful when combined with data-driven analysis methods [44], [45]. Automated pattern recognition can reveal interconnections in process behavior that would remain hidden under conventional supervision, supporting proactive optimization [11]. Ganthavee and Trzcinski [43] show how models built on historical and real-time data can predict maintenance needs, helping to prevent failures and keep plant operation stable.

4.1 Critical Synthesis and Limitations

The optimization literature reviewed here reports process-efficiency and resource-saving gains from real-time, data-driven optimization, but the magnitude of these gains varies considerably across studies and is rarely benchmarked against a common baseline, making cross-study quantitative comparison difficult. Many of the reported models are also validated on data from a single plant or a narrow range of operating conditions, which raises questions about how well the predictive gains generalize to other effluent compositions or scales of operation. This is a methodological limitation of the underlying evidence, not merely a gap in reporting, and should be considered when interpreting the optimization claims.

5. CONTROL TECHNOLOGIES

Effective control is central to the performance of wastewater treatment processes. Traditional control methods have notable disadvantages: dependence on human intervention, inadequate response speed, and limited capability to handle complex, nonlinear systems [46]. Several advanced control technologies have been developed to address these weaknesses. Model predictive control (MPC) is considered one of the major advances in control engineering for this domain [15]. MPC uses mathematical models to anticipate a system's future behavior [47], allowing control actions to be optimized in real time and helping maintain stability and efficiency under changing effluent conditions [48]. This predictive capability is particularly valuable when effluent composition varies significantly over time; whereas conventional control may fail to sustain optimal operation under such variability, MPC adjusts set-points dynamically and thereby improves process efficiency.

Adaptive control systems represent a further advance, adjusting their behavior as process dynamics change. This is particularly useful in wastewater treatment, where operating conditions vary considerably [49]; adaptive control supports the tuning of variables such as chemical dosage and aeration in response to those changes [50]. Zamfir et al. [12] provide evidence of a persistent trend toward integrating AI and ML into

advanced control systems for industrial wastewater treatment. Such systems process continuous sensor data streams and adjust parameters with reduced reliance on manual control. Shen et al. [48] report improved accuracy of chemical dosing when data-driven learning of the control strategy is used instead of predetermined rules, and Ganthavee and Trzcinski [43] report that machine learning can help recognize early indicators of impending treatment failure, supporting timely intervention and reducing unplanned downtime.
Liu et al. [21] highlight the predictive capability of intelligent systems in managing variability in effluent characteristics; anticipating changes in pollutant load can support optimization of aeration, dosing, and energy consumption while limiting chemical use [41]. Taken together, the reviewed literature suggests that AI-assisted control can help address operational uncertainty in modern industrial wastewater treatment facilities, though several obstacles remain. MPC, adaptive control, and AI-assisted control require new hardware and additional staff training, which can be a significant barrier in resource-constrained settings [46], and connecting supervisory control networks to digital platforms raises legitimate concerns about data security and system vulnerability [51].

5.1 Critical Synthesis and Limitations

Comparing across the control strategies reviewed, MPC and adaptive control are generally reported to outperform fixed-rule (conventional) control on set-point tracking and disturbance rejection under variable influent conditions, while AI/ML-based control is reported to offer further gains specifically in dosing accuracy and early fault recognition, at the cost of requiring larger volumes of historical operating data to train reliably. However, direct, like-for-like quantitative comparisons between these three families of control strategy are uncommon in the underlying literature; most studies benchmark a single method against a conventional baseline rather than against competing advanced methods, which limits the strength of comparative conclusions that can be drawn. The evidence on cybersecurity risk associated with networked control systems is similarly still emerging and is not yet matched by an equally mature body of evidence on mitigation effectiveness in industrial wastewater settings specifically.

6. AUTOMATION TECHNOLOGIES

Automation technologies have transformed industrial wastewater treatment, improving the efficiency, accuracy, and reliability of plant operations [13]. Programmable logic controllers (PLCs) remain one of the major innovations in this context; they are widely characterized as reliable solutions for coordinating pumps, valves, and other mechanical systems in response to sensor signals, supporting precise dose adjustment, flow regulation, and filter control [9]. The versatility and real-time responsiveness of PLCs are recognized as key strengths for maintaining stable treatment operations [9]. SCADA systems have evolved alongside PLCs to extend the scope of process control: SCADA collects and displays plant-wide data on parameters such as pH, dissolved oxygen, and COD, supporting remote monitoring and rapid decision-making [9]. Early detection of abnormalities by SCADA systems has been shown to reduce downtime and support regulatory compliance [11].
More recently, the role of PLC and SCADA systems has been extended through integration with IoT technology [52], enabling more effective data collection and analysis across multiple connected devices and sensors in the treatment plant. This provides a larger volume of data for real-time decision-making and can support automatic adjustment of the treatment process in response to detected changes in effluent quality [19]. Integrating IoT with automation technology can therefore improve operational efficiency while helping to reduce environmental impact, though the extent of these gains is plant- and context-specific rather than universal.

Table 2. Applications of robotics in industrial effluent treatment

Application	Description	Refs.
Automated sampling and analysis	Robots collect wastewater samples and perform real-time analysis, reducing manual labor.	[53], [54]
Pipe and tank cleaning	Robots equipped with cleaning tools support pipe and tank maintenance, particularly in confined spaces.	[55], [56]
Leak detection and repair	Autonomous robots identify leaks in pipelines and tanks, enabling earlier detection and repair.	[57]
Sludge management	Robotic systems assist with sludge removal and handling, improving efficiency and worker safety.	[58], [59]
Remote monitoring and inspection	Robots inspect hard-to-reach areas, providing live footage and data to operators.	[60], [61]
Chemical dosing	Robots support precise dosing of treatment chemicals,	[62], [63]

Application	Description	Refs.
automation	optimizing usage and reducing waste.	

6.1 Critical Synthesis and Limitations

The automation literature indicates a clear division of labor between PLC/SCADA systems, which remain the operational backbone for deterministic, rule-based control, and IoT/AI layers, which are increasingly used to make that backbone more responsive rather than to replace it. Robotics applications (Table 2) are reported mainly in narrowly scoped tasks - sampling, cleaning, inspection, and dosing rather than as fully integrated, end-to-end automated treatment lines. Claims of full automation in this literature should accordingly be read as automation of specific sub-tasks rather than of the entire treatment process. Reported evidence on the reliability of robotic systems in continuous industrial (as opposed to pilot or demonstration) settings is still relatively limited, which constrains conclusions about their maturity for widespread deployment.

7. INTEGRATION OF TECHNOLOGIES

Integrating monitoring, control, and automation systems creates a more consistent, efficient, and responsive approach to industrial wastewater treatment than any of these elements can achieve in isolation [64], [65]. This integration draws on the complementary strengths of multiple technologies, helping plants operate more effectively while working toward compliance with environmental regulations and lower operating costs. Table 3 compares conventional treatment systems with integrated treatment systems.

Among the benefits associated with integration are synergistic effects between linked systems [66]. Linking IoT sensors with AI-based control, for example, can support real-time monitoring of plant conditions alongside predictive adjustments informed by historical and real-time data. IoT devices supply a continuous flow of information on parameters such as pH, enabling more coordinated operation than would be possible with isolated monitoring, control, and automation functions.

A holistic, integrated approach can increase the efficiency and reliability of wastewater management relative to conventional processes in which monitoring, control, and automation function separately [67]. In an integrated system, IoT sensors feed data to AI-based control, which is then implemented through automated systems such as PLCs and SCADA. This coordination can support high plant efficiency with lower resource consumption and reduced environmental impact from effluent discharge.

Regulatory compliance is frequently cited as a major benefit of technological integration, since integrated systems can supply the information needed to help keep effluent within permissible limits and can flag discrepancies between plant performance and regulatory requirements more quickly than periodic manual checks. It is important to note, however, that integration reduces rather than eliminates compliance risk: automated monitoring and control lower the probability and latency of undetected excursions, but they do not remove the need for periodic verification, calibration, and human oversight. Several chemical-processing case studies report improved process efficiency and environmental performance following integration of IoT, AI, and robotics [68], though such case studies are typically single-site and are not yet matched by a comparable body of controlled, multi-site evidence.

Table 3. Comparison of traditional and integrated treatment systems

Aspect	Traditional treatment systems	Integrated treatment systems	Refs.
Monitoring	Manual or periodic monitoring with basic instruments.	Continuous, higher-frequency monitoring using IoT sensors, providing more granular data.	[69], [70]
Control	Fixed control strategies; manual adjustments based on operator experience.	AI-driven predictive control with real-time data analysis for dynamic adjustment.	[71], [72]
Automation	Limited automation; key decisions and maintenance rely on human operators.	Substantially automated sub-processes using PLCs, SCADA, and robotics, with reduced (not fully eliminated) reliance on human input.	[73], [53]
Data management	Data recorded manually, often not integrated across systems.	Centralized data collection and analysis, combining real-time and historical IoT data.	[19], [74]
Efficiency	Reactive adjustments; often less resource-efficient.	More proactive, optimized processes that can reduce	[75], [76]

Aspect	Traditional treatment systems	Integrated treatment systems	Refs.
		resource use and operating cost.	
Regulatory compliance	Compliance managed through periodic checks; higher risk of undetected breaches.	Lower regulatory risk through more continuous monitoring and control, though periodic verification remains necessary.	[77]
Environmental impact	Higher environmental risk due to slower response to system changes.	Generally reduced impact through faster, automated responses to real-time data.	[78], [79]
Maintenance	Requires regular manual intervention; more prone to error and downtime.	Partly automated maintenance supported by robotic systems, which can reduce (but not eliminate) downtime.	[80], [19]
Cost	Higher operating costs from inefficiencies and labor requirements.	Potential for lower operating costs through process optimization, though offset by higher upfront capital cost.	[81], [82]

7.1 Critical Synthesis and Limitations

The comparative picture in Table 3 is consistently favorable to integrated systems across monitoring frequency, control responsiveness, and data centralization, and this pattern is corroborated across a reasonably broad set of independent studies [69]-[82]. The evidence is less conclusive on net cost, since reported operating-cost savings must be weighed against the higher upfront capital expenditure of integrated systems, and few of the reviewed studies report a full life-cycle cost comparison. Overstated framing describing integration as delivering "full automation" or "continuous compliance" is common in the secondary literature but is not well supported by the underlying primary studies, which more accurately describe integration as substantially reducing, rather than eliminating, manual intervention and compliance risk. This distinction is maintained throughout the present review.

8. CHALLENGES AND FUTURE DIRECTIONS

A major challenge in implementing advanced technologies such as IoT-based monitoring, AI-driven control, and robotic automation is the high upfront cost [83]. Table 4 summarizes the principal challenges identified in the reviewed literature and the corresponding solutions proposed by their authors. The equipment and infrastructure required for advanced technology deployment can be prohibitively expensive for small and medium-scale operators [84]. This can be alleviated through financial incentives such as subsidies, grants, and public-private partnerships, and through participation in research collaborations that provide access to the latest technologies. A further obstacle relates to the reliability of IoT sensor data: poorly calibrated or malfunctioning sensors degrade data quality [85]. Regular maintenance and calibration, self-diagnosing devices, and redundant sensor networks that allow cross-checking of readings can help mitigate this risk. The growing use of IoT and AI also raises cybersecurity concerns, since connected systems are susceptible to hacking and cyberattacks that could compromise plant operation and the integrity of environmental data. Robust cybersecurity measures, including data encryption and, in some proposals, blockchain-based data handling, can help build a more resilient data infrastructure. Regulatory compliance presents an ongoing challenge as environmental standards evolve; adaptive control systems capable of updating alongside regulatory change, supported by AI algorithms, can help industries maintain compliance.A further constraint is the shortage of personnel with the skills needed to operate advanced monitoring, control, and automation systems; specialized staff training and recruitment of technically skilled personnel can help address this gap. The absence of standardized protocols across IoT devices, AI software, and control systems from different vendors is a related obstacle, contributing to interoperability problems that specialized training alone cannot resolve.

Table 4. Challenges in implementing advanced technologies and proposed solutions

Challenges	Proposed solutions
High implementation costs for advanced technologies	Government subsidies and financial incentives; public-private partnerships.
Data quality and sensor reliability issues	Regular sensor maintenance and calibration; deployment of

Challenges	Proposed solutions
	self-diagnostic and redundant sensors.
Cybersecurity threats in connected systems	Robust cybersecurity protocols; blockchain-based approaches for secure data handling.
Regulatory compliance changes and adaptation	Adaptive, AI-assisted control systems that can be updated alongside regulatory change.
Lack of skilled personnel to operate advanced systems	Specialized staff training programs; recruitment of technically skilled personnel.
Integration of heterogeneous IoT and AI platforms	Standardized, open-source frameworks to improve cross-vendor compatibility.

Several trends have gained visibility in the most recent literature (2024-2026) and are likely to shape the next generation of industrial effluent treatment systems.Recent work has begun to model decentralized wastewater resource-recovery and treatment systems more holistically, pointing toward digital-twin-style representations that support scenario testing and predictive operation ahead of physical implementation [40]**.** Reviews published in 2026 describe AI-driven smart treatment frameworks tailored to specific effluent types, such as aquaculture effluent, extending general-purpose AI/ML control concepts toward sector-specific application scenarios [17]**.** Fusion architectures combining variational autoencoders with recurrent networks (e.g., VAE-LSTM) have recently been applied to anomaly detection in wastewater treatment systems, offering a more sensitive complement to threshold-based SCADA alarms [21]. Recent work also situates wastewater treatment automation explicitly within the broader Industry 4.0 and sustainability agenda, framing IoT, AI, and automation less as isolated tools and more as components of a unified smart-manufacturing paradigm [65]. Reviews of sensor fault diagnosis and mitigation suggest that development of reliable and self-monitoring sensors will be a requirement for accurate continuous monitoring [85]. Taken together, these recent developments suggest that the field is moving from demonstrating individual technologies toward integrating them within broader digital-twin and Industry 4.0 frameworks, with a corresponding increase in attention to data reliability, cybersecurity, and cross-vendor interoperability.

Future development in industrial effluent treatment is likely to be oriented toward deeper integration of AI, ML, and IoT to support real-time data analysis, predictive maintenance, and control, with the aim of improving treatment efficacy, regulatory compliance, and cost efficiency. Increased use of robotics and autonomous systems can reduce reliance on manual intervention and improve process consistency, while sustainable practices such as renewable-energy integration and closed-loop recycling can help reduce environmental impact. The trajectory of the field points toward increasingly autonomous, self-optimizing systems that use real-time data to guide operation; however, based on the evidence reviewed in this paper, near-term deployments are more accurately characterized as human-supervised and progressively automated rather than fully autonomous, and claims of complete self-optimization should be treated with appropriate caution until supported by longer-term, multi-site operational evidence.

9. CONCLUSION

Advances in monitoring, control, and automation technologies have opened a new phase in industrial effluent treatment, helping address longstanding limitations of conventional wastewater management. These technologies support process optimization, improved decision-making, and reduced reliance on manual intervention. Despite this progress, several barriers continue to constrain widespread adoption, including high initial costs, sensor reliability, cybersecurity, and the availability of appropriately skilled personnel. Government incentives, improved sensing technology, stronger cybersecurity measures, and workforce training are recommended as mitigation strategies. Looking ahead, the field is moving toward greater integration of these technologies into increasingly automated, data-driven systems; based on the evidence reviewed, this trajectory is more realistically framed as progressive, human-supervised automation than as an imminent, fully self-optimizing end state. As industries continue to adopt these technologies, the treatment process can be expected to become progressively more efficient, provided the data-quality, cost, and workforce barriers identified in this review are addressed.

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