Application of AI-based techniques for anomaly management in wastewater treatment plants: a review

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Review

Application of AI-based techniques for anomaly management in wastewater treatment plants: A review

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ABSTRACT

Effective anomaly management of wastewater treatment plants (WWTPs) is crucial for environmental conservation and public health security. Traditional monitoring methods often struggle with challenges such as multivariate coupling, nonlinear dynamics, and external interferences inherent in wastewater treatment processes, which has driven growing interest towards artificial intelligence (AI)-based anomaly management solutions. This paper critically reviews recent advancements in AI-based anomaly management strategies for WWTPs, emphasizing three integral aspects: sensor data quality control and self-calibration, early anomaly detection and diagnosis, and fault-tolerant control and resilience enhancement. Systematic comparisons are made among supervised, unsupervised, and transfer learning methods, highlighting the strengths and weaknesses of deep learning, ensemble learning, and intelligent optimization algorithms in addressing practical engineering issues such as sensor noise, multimodal data distributions, imbalanced datasets, and limited cross-facility generalizability. The review further highlights real-world performance metrics beyond conventional accuracy, such as application scalability, anomaly detection timeliness, and technological adaptability. Key findings reveal research gaps hindering for the progress and application of AI-based anomaly management approaches in model interpretability, computational intensity, data quality controls, cross-facility generalization, and cost-effectiveness. More importantly, future research directions cover adaptive learning techniques, explainable AI, integration of AI with digital twin platforms, lightweight infrastructures for real-time edge computing, and environmental and economic analysis of AI deployments in WWTPs.

1. Introduction

Wastewater treatment plants (WWTPs) need to be highly efficient and operationally flexible with the employment of advanced treatment processes and management strategies, which are capable of addressing different water quality and external disturbance conditions in order to consistently comply with treatment standards (Cairone et al., 2024; Cassidy et al., 2020; Pandit and Sharma, 2024). A comprehensive and stable wastewater treatment process enabled by efficient management is essential in protecting ecosystems and maintaining public health (Obaideen et al., 2022). It ensures effective elimination of pollutants, prevents harm to ecosystems, and avoids risks from harmful substances to human health (Silva, 2023).

However, wastewater treatment plants consistently face anomalies, as illustrated in Table 1, such as large fluctuations in water quality parameters (e.g., Chemical Oxygen Demand (COD), Biochemical Oxygen Demand five-day (BOD_5), pH), process malfunctions (e.g., sludge bulking, abnormal conditions of aeration equipment or membrane system, or equipment such as sensor and pump failures), or external environmental disturbances (e.g., intensive rainfall or seasonal flow and temperature changes) (Bellamoli et al., 2023; Liu et al., 2023d). Delayed detection and inefficient management of such anomalies can negatively affect system stability, process efficiency, and effluent conformity, causing serious economic and environmental impacts (Chandola et al., 2009).

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Thus, timely detection of anomalies, accurate diagnosis, and immediate remedial action have become the main technology requirements in wastewater treatment implementation (Wang et al., 2025).

Anomaly management in WWTPs is an integral lifecycle framework with three closely related aspects: sensor data quality management and self-calibration, early anomaly detection and diagnosis, and fault-tolerant control and resilience enhancement (Liu et al., 2023d; Wang et al., 2025). These complementary aspects together can maintain the robustness and operational stability of wastewater treatment systems. Early anomaly detection and diagnosis prioritise the use of online monitoring, big data analytics, and intelligent diagnostic techniques to promptly detect and accurately identify anomalies so that timely corrective actions can alleviate the impact of faults, ensuring compliance and safe operation (Bellamoli et al., 2023; Cassidy et al., 2020). Conversely, fault-tolerant control and resilience enhancement aim to enhance system adaptability and recovery through redundancy designs, rapid response mechanisms, and optimized operation strategies. This will help WWTPs achieve stable operation or rapid recovery in situations such as water quality fluctuations, equipment failures or extreme weather events (Fasanotti et al., 2018; Z. Liu et al., 2024). Moreover, sensor data quality management and self-calibration provide the fundamental support for the above two aspects by combining multi-sensor data fusion, anomaly detection, and dynamic calibration techniques to effectively eliminate hazards of data distortion and improve the accuracy and responsiveness of the anomaly detection systems (Ba-Alawi et al., 2023a; Yan et al., 2019). These three aspects collectively form a closed-loop process to ensure effective, safe, and sustainable operation of wastewater treatment systems (Khurshid and Pani, 2023; D. Yang et al., 2024a), as shown in Fig. 1.

The conventional anomaly monitoring approaches usually adopt fixed-threshold strategies or rule-based systems, which are difficult to use in addressing the complex dynamics of wastewater treatment. For example, wastewater treatment processes are characterized by nonlinear coupling interactions between numerous variables, which restrict the effectiveness of linear or simple statistical models in real-world anomaly management (Alvi et al., 2023). Furthermore, external disturbances such as heavy rains or industrial discharges make anomaly detection and diagnosis more difficult. As a result, increasing research in recent years has focused on exploring AI-based solutions to anomaly management in wastewater treatment plants. These solutions aim to utilize the advanced data processing and pattern learning capabilities of AI. Specifically, AI models can be trained with historical monitoring data to distinguish normal and abnormal states and, more importantly, identify anomalies in real time with higher accuracy and reliability (Bahramian et al., 2023; Duarte et al., 2024).

Although a few review studies have examined the current state of AI applications in wastewater treatment anomaly detection systems (Khurshid and Pani, 2023; Liu et al., 2023d; Wang et al., 2025), as summarized in Table 2, they primarily focus on specific scenarios such as benchmark simulation models (e.g., BSM1 for biological treatment processes) or isolated process fault detection cases. Existing review studies that mainly summarize approaches based on mechanistic models and theoretical scenarios can no longer meet the needs of current technological development, as the methods covered in these reviews often struggle to accurately capture and identify anomalies under complex, real-world operational conditions. More importantly, these studies have not thoroughly addressed the integrated application scenarios and practical challenges across the full anomaly management lifecycle. In contrast, a review exploring the diverse operational conditions based on real-world operational data found in real, industrial-scale WWTPs can be more meaningful for guiding future research.

There are noticeable research gaps, in particular regarding cross-facility generalizability, real-time responsiveness, and the cost-effectiveness of AI-based systems (Ba-Alawi et al., 2023a; D. Yang et al., 2024a). The current study intends to systematically review and critically summarize recent developments and applications of AI-based approaches to anomaly management based on industrial-scale WWTP data and theoretical simulations, specifically evaluating their contribution in critical phases such as self-calibration of sensors, anomaly detection and diagnosis, and fault-tolerant control to increase the system's robustness. Moreover, the applicability, merits, limitations, and deployment aspects of different AI approaches are highlighted in real-world applications, including supervised learning, unsupervised learning, transfer learning, ensemble learning, and other AI-based algorithms. The current study presents the first review systematically investigating AI-based approaches in the full anomaly management cycle in WWTPs.

The objective of this paper is to offer theoretical insights and technological advice for promoting smart transformation in the wastewater treatment industry while also addressing the current literature gaps by focusing on true industrial application contexts, methodological generalizability, and cost evaluations, thus specifying the directions of future research accordingly.

2. Research design and bibliometric analysis

This paper systematically summarizes and examines literature from the last decade (2015–2024) in the field of anomaly management in wastewater treatment systems using AI. The literature review is focused on three important lifecycle phases: data quality and self-calibration of sensors, anomaly detection and diagnosis, fault-tolerant control and resilience enhancement. Research specifically on forecasting water

Table 1
Description of common anomalies in wastewater treatment plants.

No.	Anomaly Type	Process Stage	Root Causes	Typical Impact	Reference
1	Influent quality shock	Pre-treatment	Storm events, industrial discharge	Overload downstream, process upset	T. Cheng et al. (2019); Xu et al. (2017); Yin et al. (2017)
2	Chemical dosing error	Primary treatment	Pump failure, human error	Insufficient/over-dosing, permit fail	Dairi et al. (2019); Q. Wu et al. (2022a)
3	Aeration system malfunction	Biological treatment	Blower breakdown, valve fault	Loss of nitrification, High NH_4^+	D. Yang et al. (2024a); Yin et al. (2017)
4	Sludge bulking	Secondary treatment	Filamentous bacteria, nutrients	High effluent solids, clarifier upset	Gulshin and Kuzina (2024); H.-G. Han et al. (2019); Xu et al. (2017)
5	Effluent ammonia/nitrogen high	Secondary/Tertiary treatment	Nitrification failure, toxic shock	Permit violation	Guo et al. (2016); Mamandipoor et al. (2020)
6	Sludge digester malfunction	Sludge treatment	Overload, toxic input, temp drop	Gas drop, unstable sludge, Odors	Y. Liu et al. (2015); Xu et al. (2017); Yin et al. (2017)
7	Sensor fault	All stages	Sensor drift, fouling, calibration	Data errors, false alarms	Mali and Laskar (2020); Newhart et al. (2024); Samuelsson et al. (2017)
8	Equipment mechanical failure	All stages	Aging, wear, electrical/mechanical	Downtime, bypass, process loss	Dairi et al. (2019); Sunal et al. (2024)
9	SCADA/communication error	All stages	Network/PLC issue	Loss of automation, operator workload	H. Han et al. (2024)

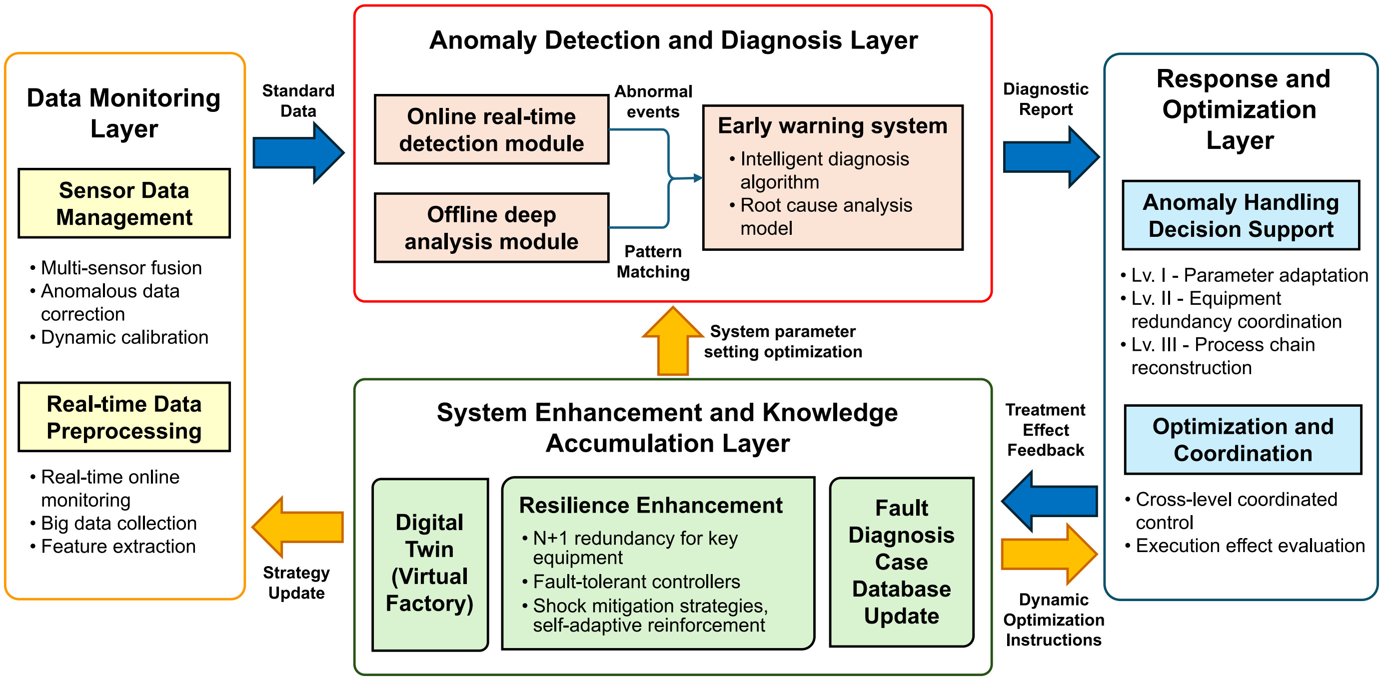

Fig. 1. Closed-loop flowchart of the anomaly management system.

Table 2
Survey of the review works focusing on anomaly management in WWTPs.

Reference	Review Focus	Target System	Technique Classification	Application Scenarios
Y. Liu et al. (2023)	AI and data analytics for fault detection, diagnosis, and prognosis	Entire urban wastewater system (sewer networks, WWTPs, and resource management)	• Data-driven approaches • Mechanistic and knowledge-based hybrid approaches • Digital Twins	Process anomalies (sludge bulking, sewer corrosion), instrumentation faults (sensor and actuators faults)
Khurshid and Pani (2023)	Machine learning for process monitoring	Biological treatment processes (Benchmark Simulation Model No. 1 - BSM1)	• Simple univariate (control charts) • Multivariate techniques • Deep learning techniques	Sensor faults (e. g., dissolved oxygen), process anomalies (reaction parameters, oxygen transfer rates, influent BOD changes)
Wang et al. (2025)	Data-driven fault detection and diagnosis methods	General wastewater treatment systems (theoretical and real)	• Multivariate statistical • Machine learning • Hybrid methods	General process faults, sensor faults

quality parameters (e.g., COD, BOD, NH_4^+, TN) under different scenarios using AI was not considered in this survey. But research on enhanced wastewater treatment process resilience and operation optimization by anomaly management was incorporated in this survey.

As illustrated in Fig. 2, the literature search was carried out with a systematic approach. Starting with relevant literature published from 2015 to 2024, a search was performed in the Scopus database. The initial search terms were different combinations of keywords such as anomaly, abnormality, irregularity, outlier(s), fault(s), deviation, and wastewater. But the first-round search generated a vast number of publications. Then in the second step (refer to Fig. 2), the search was narrowed down with the addition of more AI-specific keywords such as artificial intelligence, machine learning, and deep learning, which significantly reduced the number of articles retrieved. From the remaining steps (includes the third, the fourth, and the fifth steps), online screening with keyword search combined with manual review through abstract reading was used to eliminate the studies mainly concerning water quality forecasts but not anomaly identification. Particularly, the studies were also screened further with the following specific criteria: (1) exclusion of the studies mainly concentrating on water quality forecasting; (2) exclusion of the papers with no clear indications of anomaly identification or related terms in wastewater treatment; and (3) exclusion of purely theoretical perspectives with no validation data. Finally, the gathered papers were systematically classified and screened once more to complete the selection. Online search engines and databases like Web of Science and Google Scholar were also cross-checked to achieve comprehensive coverage and correct categorization of the related literature.

2.1. Bibliometric analysis

In this study, bibliometric analytical techniques such as keyword clustering analysis, thematic evolution analysis, and publication trend analysis were utilized to indicate research hotspots and trends in the topic of AI-based anomaly management in wastewater treatment systems. This research ensured rigour and reproducibility by using VOSviewer software to carry out keyword co-occurrence analysis, create a clustering diagram and keyword time evolution diagram, and statistically plot the number of publications and trend diagram using Excel tools.

The keyword co-occurrence network (shown in Fig. 3) illustrates research hotspots and thematic distributions for the application of AI to anomaly detection and diagnosis in wastewater treatment. Keywords in the graph are grouped into three different clusters, represented by green, red, and blue. The green cluster focuses on keywords including "anomaly detection/diagnosis", "process control", and "learning systems" and shows that research emphasis is placed on the use of data-driven anomaly detection techniques and intelligent optimization strategies (e.g., principal component analysis, Bayesian networks, autoencoders) for monitoring and diagnosis of wastewater treatment processes. The red cluster highlights keywords including "machine learning", "deep learning", "forecasting", and "water quality" and displays the key role

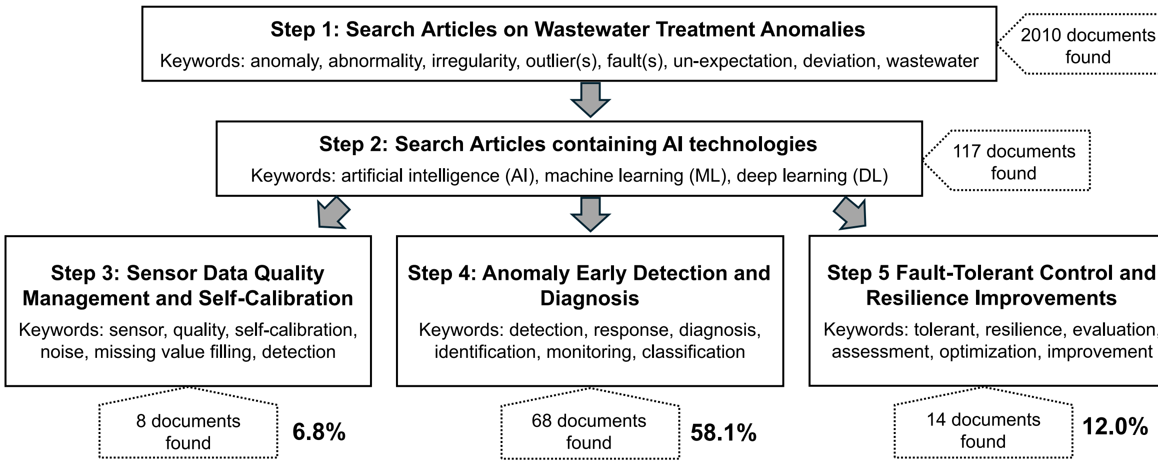

Fig. 2. Flow diagram of the search and screening for key references.

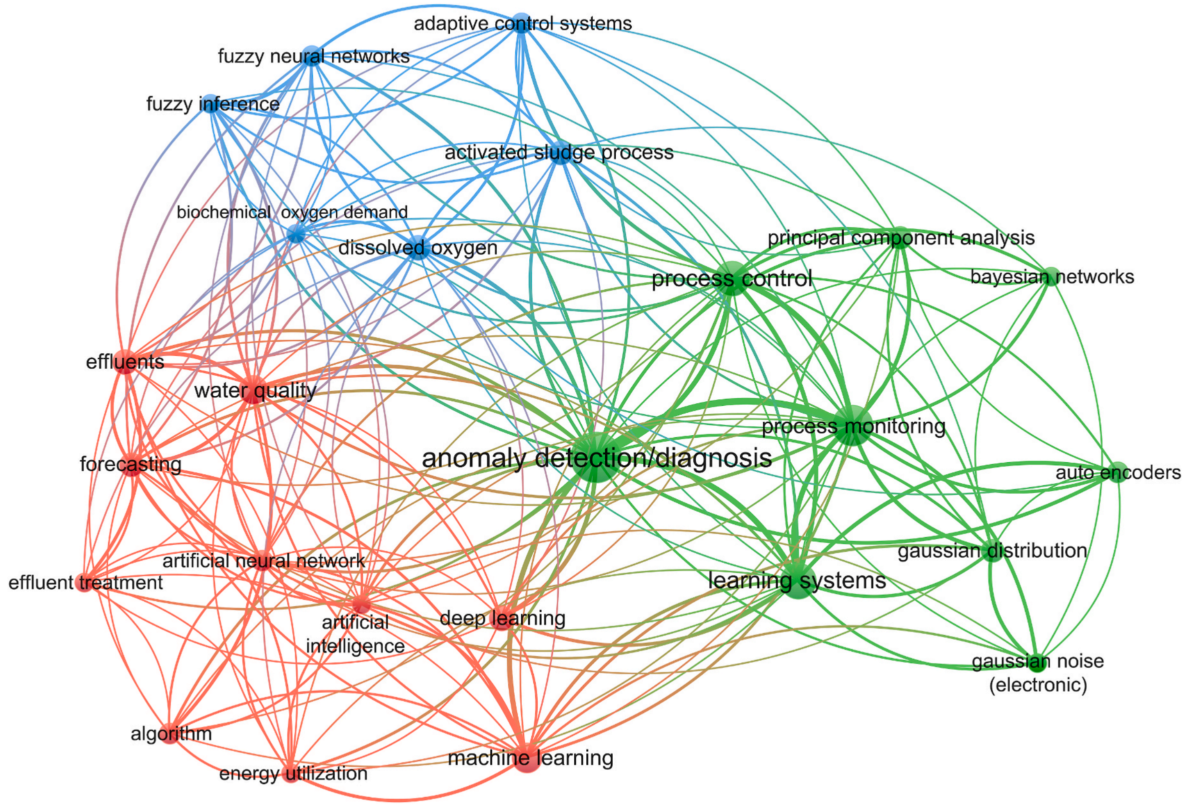

Fig. 3. Keyword clustering diagram based on research themes.

played by deep learning and machine learning techniques in forecasting water quality, energy management, and algorithm development. The blue cluster includes keywords like "fuzzy neural networks", "dissolved oxygen", and "activated sludge process" and reflects the current applications and development status of fuzzy control and neural network techniques for monitoring key process parameters in wastewater treatment. Generally, the clustering of keywords has revealed the hot areas of prior research and the distribution of multi-dimensional AI applications in wastewater treatment and indicates a vast research value on integrating these subject clusters in subsequent studies.

From the timeline diagram (shown in Fig. 4), we can further understand the temporal development of research keywords in wastewater treatment anomaly detection. Even though "process control" and "learning systems" have always occupied the main role in the theme of "anomaly detection/diagnosis", the methodologies involved have changed from classical algorithms such as "artificial neural network", "fuzzy inference", "principal component analysis" and "Bayesian networks" to data-driven approaches like "fuzzy neural networks" and "machine learning" and more advanced AI-driven ones like "deep learning" and "autoencoders" in recent years. Particularly, research related to the keywords "forecasting", "adaptive control system", "deep learning" and "autoencoders" has significantly increased since 2021, which reflects an important research transformation from the development of single AI algorithm to the development of intelligent optimization and real-time control (RTC) systems.

In addition, the publication trend analysis (2015–2024) illustrated in Fig. 5 reveals a sharply rising research interest in the field of AI-based anomaly detection in WWTPs. Fault-tolerant control research has also

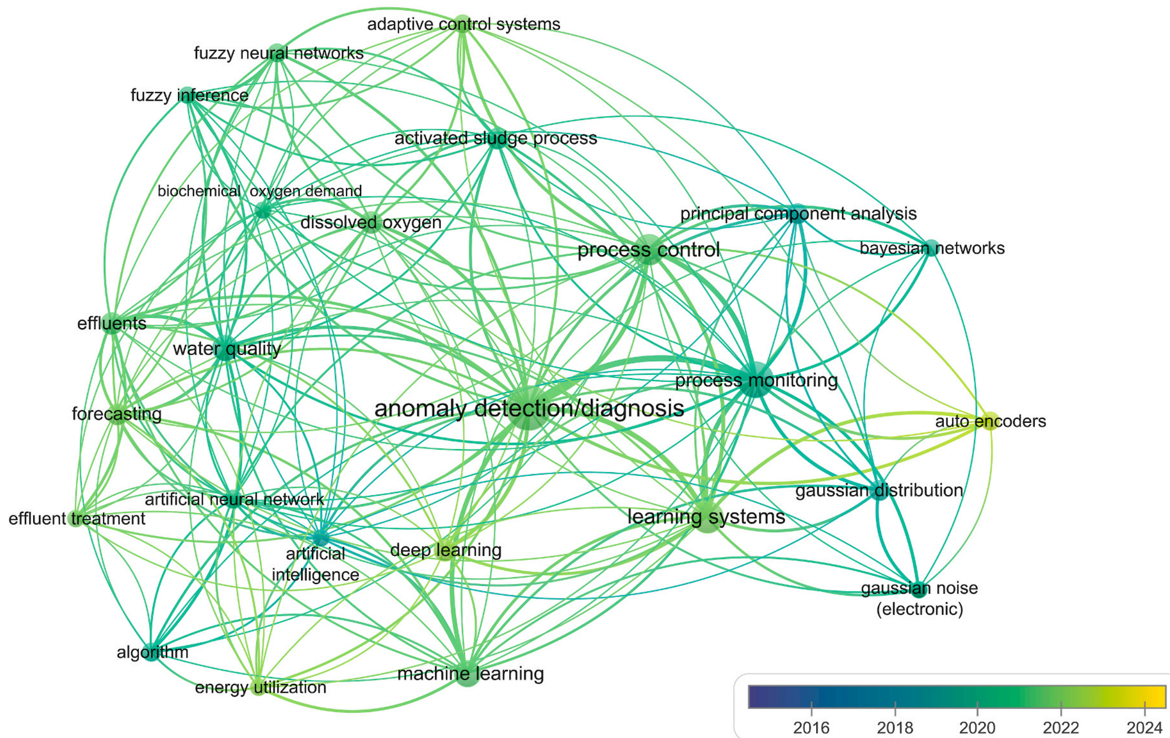

Fig. 4. Temporal evolution of keywords in timeline diagram.

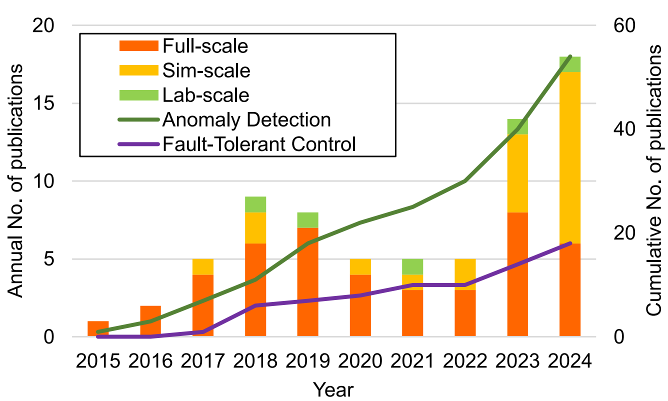

Fig. 5. Annual number of publications (bars) and cumulative number of publications (lines) on AI-based anomaly management in wastewater treatment plants from 2015 to 2024. The stacked bars represent the annual number of publications by dataset type (Full-scale, Sim-scale, Lab-scale) used in each study. The green and purple lines show the cumulative number of publications related to "anomaly detection" and "fault-tolerant control", respectively.

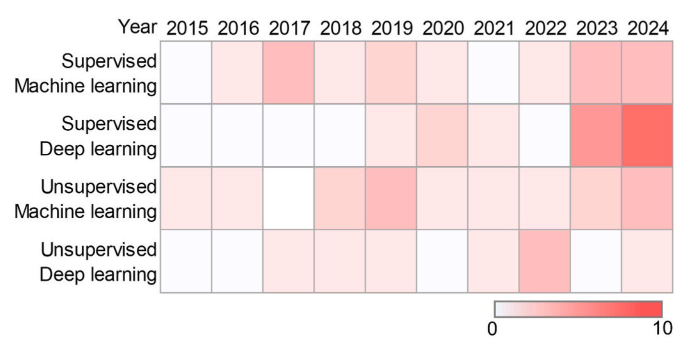

Fig. 6. Heat map of publications for AI model types.

gradually increased, but more slowly, presumably because of its complexity and implementation issues. Also, more simulation-scale and laboratory-scale research has emerged probably due to a cost-effectiveness preference, increased flexibility, and faster iteration enabled by advances in technology. However, the approaches proposed by simulation-scale studies are generally not adequate for industrial application in full-scale WWTPs, thus bridging the gap between theoretical validation and industry deployment remains a key issue for upcoming research.

The heat map of different types of AI (in Fig. 6) indicates that supervised learning is used most extensively in wastewater anomaly detection with the highest intensity over different years. Deep learning has also attracted strong interest in recent years as the industry looks to use the power of deep neural networks to improve the accuracy and reliability of anomaly detection. Some areas with lower intensity may offer opportunities for deeper research in the areas of adaptive decision-making and intelligent optimization, which means the drive to innovate and apply AI is not fading but continuing.

On the basis of the above bibliometric analysis, studies of anomaly management in wastewater treatment are increasingly shifting from early algorithm verification to systematic intelligence optimization and operational real-time control. Multi-method combination with AI technology is becoming the research trend in the mainstream, and emerging AI approaches like explainable AI and reinforcement learning that have not yet attracted sufficient research attention currently have tremendous potential and can become the new research frontier in solving complex decision-making issues.

3. Discussion

3.1. Sensor data quality management and self-calibration

With the large-scale application of sensors in WWTP equipment, sensor failure, drift, noise, and dirt blockage often lead to data distortion or loss, which in turn affects process control and decision optimization.

In order to solve these problems, researchers have begun to explore the introduction of AI, as shown in Table A.1, to improve the integrity and credibility of sensor data through methods such as anomaly detection, data interpolation, and automatic calibration.

Considering the differences in core technical frameworks and application scenarios, the studies in this area can be roughly divided into four categories. The first category is the time series deep learning method based on Long Short-Term Memory (LSTM) autoencoder (AE), which focuses on using the recurrent neural network structure to capture the complex dependencies of time series and performs well in short-term anomaly correction and prediction, such as a parallel model combining particle swarm optimization (PSO) with LSTM (Yan et al., 2019), and short-term and long-term dynamic LSTM-AE models (Seshan et al., 2024). The second category is multi-task learning and explainable AI-based approaches, which can not only complete fault diagnosis and data reconstruction in parallel in the same network, but also provide more intuitive diagnostic bases through attention mechanisms and explainable AI (XAI) models, e.g. explainable deep multi-task learning autoencoder network (DMTL-UNet) (Ba-Alawi et al., 2023a), and multi-sensor fusion-based automated data reconciliation and imputation (MSF-ARI) (Ba-Alawi et al., 2023b). Their study found that multi-task explainable AI technology can be used to enhance fault-diagnosis efficiency with an F1 score up to 99.08 %, and gain energy consumption reduction of 37.44 % compared to conventional methods. The third category is unsupervised learning methods. For example, Local Outlier Factor (LOF) and self-organizing map (SOM) are applied to solve scenarios with missing or insufficient large-scale annotations and can provide high-precision anomaly detection and data interpolation when the missing rate is not high (Hansen et al., 2022; Mng'ombe et al., 2023). The fourth category is the fusion of deep neural networks and probabilistic models, among which the stacked denoising autoencoder (SDAE) and variational autoencoder based on a deep residual network structure (ResNet-VAE) show robustness and generalization potential in multidimensional nonlinear anomalies and high-noise environments by integrating deep representation learning with distribution modelling (Ba-Alawi et al., 2021, 2022). Ba-Alawi et al. (2022) applied the VAE to model the complex, non-Gaussian distribution of process data, which achieved better identification of sensor faults and reconstruction of faulty signals. They successfully predicted missing sensor readings with their VAE model through the synthesis of data compatible with learned distributions. The above models have been successfully verified with actual wastewater treatment plant data and are generally superior to traditional statistical or shallow machine learning methods in terms of the model's reconstruction and imputation performance measurements, as shown in Table A.1.

As can be seen from Fig. 7, when applying AI models in missing data interpolation and faulty data reconciliation for sensors in wastewater treatment processes, there are quite different performances among each model, with mean absolute percentage error (MAPE) used to measure the differences. In the imputation of missing data, the ResNet-VAE model performed excellently, particularly for the internal sludge flow (Qr), with the MAPE as low as 1.04 %, but for the dissolved oxygen (Do-aer) in the aerobic pool, its performance declined sharply (the MAPE was as high as 10.44 %). However, the Parallel PSO-LSTM model kept a well-balanced and credible ability to fill the data for the entire set of parameters, with the MAPE ranging between about 5 % and 7 %. In the faulty data reconciliation scenario, the MAPE differences between the different AI models increased significantly, due to the higher complexity involved in processing faulty sensor data. For example, the DMTL-UNet model, even with its improved interpretability and fault diagnosis ability, presented comparatively high MAPE values, especially for influent total nitrogen (TN-in) at 20.31 %. The SDAE model was comparatively more robust with MAPE ranging from 12 % to 14 %, indicating its potential in the multidimensional anomaly correction process. These results reflect the need to carefully select AI models according to specific parameter requirements and targeted application scenarios with a proper balance between accuracy, robustness, and computational cost. Nevertheless, a more important issue has also been revealed, that the quantitative comparative evaluation of different models remains a key bottleneck in this research field.

3.2. Anomaly early detection and diagnosis

The evolution of AI-based anomaly detection methods is a progression from simple statistical methods towards more complex and computationally costly AI-driven techniques. Classical methods like PCA and ICA prevailed because of computational simplicity and interpretability but were limited in accuracy and flexibility. Supervised and unsupervised learning algorithms improved the performance of anomaly detection and classification, and the adaptability of extensive data inputs with new challenges in computational intensity, model interpretability, and high-quality data. Hybrid methods combining the

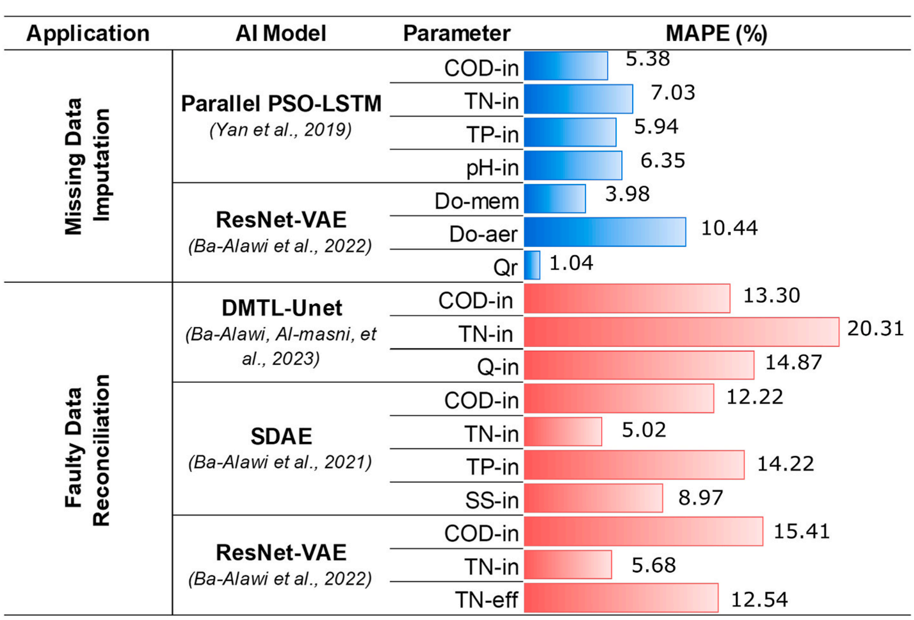

Fig. 7. MAPE of different AI models for sensor data quality management and self-calibration.

robustness of classical statistical methods and the power of deep neural networks to balance accuracy, efficiency, and interpretability are a recent trend.

3.2.1. Supervised learning-based AI methods

Wastewater treatment processes usually exhibit characteristics such as nonlinearity, dynamic coupling, and complex data noise. Therefore, compared to traditional anomaly detection methods based on mechanistic models or simple statistical assumptions, supervised learning-based AI models offer a promising alternative by utilizing prior label information. This section reviews the application scenarios and performance results of anomaly detection strategies based on such models (see Table A.2), and further detailed discussions are given below.

Some early studies have adopted supervised classical machine learning methods such as locally weighted projection regression (LWPR), relevance vector machines (RVM), and Gaussian process regression (GPR) to address challenges related to multivariable coupling and data imbalance in wastewater treatment monitoring. LWPR has been applied to nonlinear process monitoring in WWTPs to improve the detection of anomalies in key parameters such as dissolved oxygen (DO), flow rates, and substrate concentrations (Yin et al., 2017). The integration of Fast RVM with pre-processing methods, specifically the synthetic minority over-sampling technique (SMOTE), was shown to notably enhance the diagnostic performance of fault classification in imbalanced wastewater treatment datasets (Xu et al., 2017). Nevertheless, the effectiveness of this approach was still affected by the underlying data characteristics and the specific modelling and pre-processing configurations, and its generalizability and industrial application prospects still need further investigation. GPR combined with sequential Monte Carlo (SMC) has demonstrated superior capability for interpolating noisy flow signals and detecting ammonium sensor drift in WWTP applications, but its effectiveness depends heavily on the selection of the kernel function, tunning of parameters, and sufficient prior knowledge of the monitored processes (Samuelsson et al., 2017). Its practical deployment should be rigorously evaluated against simpler methods.

In contrast to deep architectures, other supervised AI approaches using shallow neural networks have also proven to be effective for fault detection in WWTPs due to their model simplicity, online adaptability, as well as robust nonlinear feature representation. For common sludge bulking faults, H.-G. Han et al. (2018) presented an intelligent approach using a self-organizing recurrent radial basis function neural network, which is effective in detecting bulking events as well as their respective reasons such as insufficient DO and high COD. Extending this, H.-G. Han et al. (2019) developed a self-organizing type-2 fuzzy neural network coupled with a target-related identification algorithm, which effectively distinguished various types of bulking depending upon real-time process data such as those caused by insufficient DO, nutrient deficiency, or inadequate sludge loading. In the interest of effective and accurate identification of anomalies under dynamic conditions, P. Chang et al. (2024) introduced a broad slow feature neural network (BSFNN) with incremental learning capability, which was effective in extracting slowly varying and nonlinear features online to fit rapid structural adjustment in real time monitoring.

Apart from shallow neural networks, ensemble learning algorithms specifically founded on gradient boosting and tree-based ensemble approaches have also attracted the interest of some researchers due to their capacity to increase robustness in classification, address data imbalance, and generalize to varied wastewater treatment conditions. In the case of small sample size and infrequent abnormal events, the CatBoost gradient boosting model was excellent in regression and classification tasks for wastewater treatment data with SMAPE values of critical effluent parameters below 10 % and a ROC-AUC value of detecting filamentous bulking events up to 1.0 (Gulshin and Kuzina, 2024). In multiclass anomaly classification of intermittent aeration wastewater treatment processes, the performances of XGBoost-SMOTE and LightGBM-SMOTE were better in comparison to other strategies with macro-recall reaching 0.84 and macro-F1-scores up to 0.72 in cross-validation experiments and maintaining satisfactory performance (macro-recall as high as 0.62) in fully independent test plants (Bellamoli et al., 2023).

In addition to the above supervised classical machine learning methods, supervised deep learning approaches have been widely applied to wastewater treatment anomaly detection and fault diagnosis due to their powerful data-driven modelling capabilities in recent years. Methods such as the time-stacked broad learning system (Time-SBLS) (Peng et al., 2023) and Gaussian mixture model (GMM) under-sampling (Zadkarami et al., 2024) have proven effective in reducing computational overheads and enabling real-time fault detection in large-scale and imbalanced datasets. An LSTM-based approach proposed by Mamandipoor et al. (2020) has significantly improved the detection of collective faults in key influent sensors within biological treatment processes by capturing complex time-series dependencies. Deep neural network architectures have been introduced as important tools for robust anomaly detection. For example, the Monte Carlo deep dropout neural network (MC-DDNN) developed by Mali and Laskar (2020) enables earlier detection of incipient sensor faults with minimal confusion with noise on both BSM2 and real industrial plant data, supporting timely maintenance by reliably identifying even low-magnitude faults that are often missed by traditional methods. Peng et al. (2021) proposed a deep recurrent network integrated with high-order statistical information (HSI-DRN) to address simultaneously nonlinear and non--Gaussian WWTP data. On the BSM1 benchmark, this method achieved average false alarm and missed detection rates as low as 0.0215 % and 0.586 % respectively. Hu et al. (2024) developed a multiscale convolutional neural network (MSCNN) that effectively captures spatio-temporal features in multivariate process data, achieving robust fault diagnosis performance in dynamic wastewater treatment environments. Some other advanced deep learning models such as YOLOv5 with histogram equalization for microbial detection (Inbar et al., 2023) and DeepLabv3+ for real-time foam segmentation (Carballo Mato et al., 2024) have been applied to visual data from WWTPs, achieving improved precision and robustness in visual anomaly monitoring. Carballo Mato et al. (2024) established an AI-driven foam monitoring system for a Moving Bed Biofilm Reactor (MBBR) process at a full-scale municipal WWTP in Spain. The system applied deep-learning models (DeepLabv3+ and OSTS) trained with operational images to automatically track foam coverage every 10 min. The segmentation performed well, showing that Dice scores were over 86 % and IoU values were above 75 %. Alerts were triggered automatically to notify operators if foam concentrations exceeded the thresholds (e.g., 20 % coverage of the surface). Practical operational improvements included a substantial reduction in maintenance frequency, approximately 15–25 % energy savings due to improved oxygen transfer efficiency, and prevention of biomass washout events. Separately, a Transformer-based model with multi-head attention (Peng and FanChao, 2024) enables effective modelling of dynamic couplings and long-term dependencies among key process variables (e.g., aeration and ammonia-nitrogen), thereby effectively reducing false alarm and missed detection rates on BSM1, which shows more promise for future applications compared with traditional RNN and LSTM.

Owing to the variation in reported evaluation indicators across studies (see Table A.2), this review predominantly uses Accuracy and Fault Detection Rate (FDR)/Recall for subsequent comparison of performances in Fig. 8. Accuracy describes the overall model classification ability, while FDR or Recall highlights its capacity to detect abnormal events. Both of them can provide complementary but limited insight into model effectiveness in the scenario of class imbalance. Fig. 8 reveals that supervised deep learning approaches that leverage temporal dependence (e.g., LSTM, Transformer) can consistently maintain good recall and accuracy, indicating superior adaptability to complex, multivariate, and big sensor datasets. For example, LSTM-based approaches had the highest recall of up to 93.9 %, which obviously outperformed traditional methods whose recall typically ranges from 73 % to 85 % (Mamandipoor

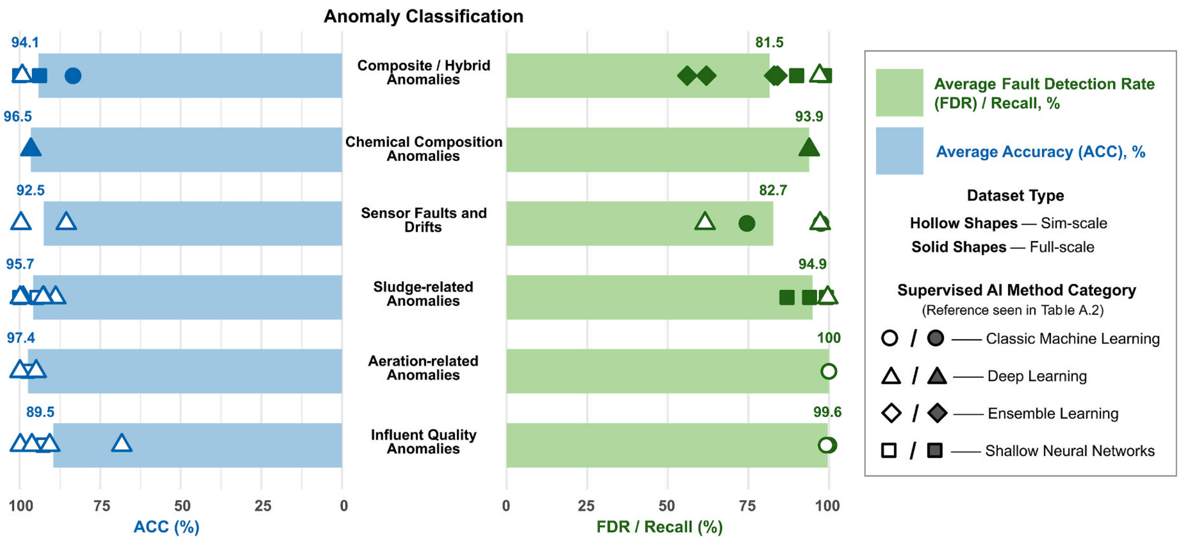

Fig. 8. ACC and FDR/Recall for supervised AI methods in wastewater treatment anomaly monitoring.

et al., 2020). Ensemble learning algorithms such as XGBoost and CatBoost also demonstrate good and well-balanced performances with both high accuracy and detection rates in imbalanced and multiclass scenarios, with accuracy improvements of 5–15 % compared to traditional methods in various case studies. By contrast, supervised classical machine learning approaches can attain competitive accuracy, but their recall or rates of detection are typically comparatively poor and fluctuate, particularly in unfavourable data conditions. For instance, the recall of SVM and Random Forest models may drop below 80 % in highly imbalanced datasets and missed alarm rates can rise above 15 %. It is worth mentioning that recent novel methods such as MC-DDNN, HSI-DRN, and MSCNN presented very low false positive and false negative rates, indicating improvements in feature extraction and uncertainty modelling.

Based on the above discussion, the advantage of supervised learning lies in its ability to utilize labelled data, which not only improves anomaly detection accuracy, but more importantly enables the classification of abnormal events and identification of root causes. This attribute provides support for operators to implement interventions and ensure the stable operation of wastewater treatment plants. Furthermore, various improvement strategies such as higher-order statistical features, multi-scale convolution, and Transformer architectures have proven feasible for reducing false positives and false negatives while enhancing the timeliness of fault identification. Although there are several evident strengths, supervised learning methods inherently present several limitations. First, labelled data were often scarce, expensive, or biased in real WWTPs, but these methods depend on the availability and quality of such data. Additionally, the computational intensity of supervised deep learning models like LSTM and Transformer makes them difficult to implement in real-time operations. Furthermore, supervised models trained with limited or imbalanced datasets can easily lead to overfitting, which can weaken generalization performance when conditions or operational environments change. Future research should therefore focus on network compression, cross-platform collaborative training, and data diversity enhancement, to facilitate large-scale implementation in WWTP anomaly management.

3.2.2. Unsupervised learning-based AI methods

Our work shows a performance comparison of different unsupervised learning-based AI approaches in recent studies on anomaly monitoring in WWTPs (see Table A.3) in terms of fault detection rate, false alarm rate, fault warning time, and application conditions. Based on the review of the above-mentioned case studies, the feasibility and limitations of unsupervised learning AI approaches for wastewater treatment anomaly monitoring under different data volumes, operating complexities, and noise levels are presented.

Unsupervised classical machine learning shows great benefits in processing multivariable-coupled, nonlinear, and high-dimensional data because of its independence from data labels. Principal component analysis (PCA) and its advanced versions, including kernel principal component analysis (KPCA) and adaptive principal component analysis (AD-PCA), can serve in dimensionality reduction, denoising, and fault identification. These methods can detect diverse sudden anomalies (e.g., aeration and influent quality variations) in real WWTPs and issue early warnings following drift faults as well as short-term anomalies (T. Cheng et al., 2019; Haimi et al., 2016; Y. Liu et al., 2015; Newhart et al., 2024). Haimi et al. (2016) implemented an adaptive PCA-based anomaly detection system in Viikinmäki WWTP, Finland's largest municipal wastewater treatment plant (800,000 population equivalents). The system continuously recalibrated PCA models using real-time operational data, effectively detecting sensor faults (e.g., ammonia sensor drift exceeding 1 mg/L) and process disturbances (such as influent suspended solids spikes from 200 mg/L to over 500 mg/L). Industrial application results exhibited fast anomaly detection and a high false alarm rate reduction from conventional static thresholds. On a practical level, the system allowed for the timely identification of declines in pH and interruption of nitrification, improving the reliability of the treatment and the stability of the operation. To improve adaptability to complex and non-Gaussian processes, some works combined genetic algorithms (GA) with Bayesian inference, or increased fault detection rates and decreased false alarm rates via adaptive selective independent component analysis (ASEICA) and multi-model fusion (Z. Li and Yan, 2018, 2019, 2020). At the same time, clustering algorithms (e.g., K-means) have exhibited distinctive merits in rapidly capturing of influent fluctuation and sludge bulking patterns (Chow et al., 2018; Navato and Mueller, 2021). Moreover, Gaussian process models maintain a balance between timely fault detection and stability (Zambrano et al., 2019), while the coupling of kernel techniques with dimensionality reduction (e.g., Improved Variable Importance in the Projection (IVIP) + KPCA with Multivariate Exponentially Moving Average (MEKPCA), Uniform Manifold Approximation and Projection (UMAP) + Support Vector Data Description (SVDD)) can further enhance the accuracy and robustness of anomaly detection for the high-dimensional data (T. Chang et al., 2024; J. Yang et al., 2023).

Deep learning-based unsupervised AI methods have been more effective in handling nonlinear, non-Gaussian, and multimodal wastewater treatment anomaly monitoring data. For instance, the use of the Enhanced Bottleneck Neural Network (EBNN) model with adaptive confidence bounds can more significantly lower false alarms in multimodal situations and detect faults in ammonia nitrogen ($NH4+$) and nitrate ($NO3-$) sensor readings compared to fixed threshold (Bouzenad and Ramdani, 2017). The Deep Belief Network (DBN) in combination with One-Class Support Vector Machine (OCSVM) provided operators with the possibility to establish anomaly warnings five days in advance under high-dimensional noisy conditions (Harrou et al., 2018). Meanwhile, the combination of a Recurrent Neural Network (RNN) and Restricted Boltzmann Machine (RBM) with an unsupervised classifier OCSVM demonstrated robust performance with the best AUC reaching 0.98 in identifying a few influent anomalies such as seawater intrusion using real WWTP data (Dairi et al., 2019). The Part Interval Stacked Autoencoder (PISAE)-SVDD model can reduce the number of false alarms and enhance the detection capabilities in complex real-world wastewater treatment processes through introducing uncertainty in the form of tolerant reconstruction errors in sensor measurements (Q. Wu et al., 2022b). Compared to baseline autoencoders, the Multi-stage Variational Autoencoder (M-VAE) can improve the detection accuracy by 37.8 % and reduce the false alarm rate to 4.83 % for sludge bulking and toxic shock faults (Peng et al., 2022a). The VAE plays a key role in modelling the probability distributions of process data for each stage and in extracting essential Gaussian features from non-Gaussian measurements. The probabilistic interpretation allows the VAE-based model to distinguish normal with faulty conditions more effectively. The combination of automatic stage-wise division with VAE-based feature learning can enable anomaly detection well across different stages in real-world WWTPs. Lastly, Ren et al. (2024) presented the idea of a DAE-PCA model that incorporates a deep autoencoder (DAE) and a learnable kernel mapping strategy as an alternative to the classical KPCA strategy. It raised fault detection rates by 4.69 % on the TE dataset and 0.27 % on the WWTP data against the baselines, with the additional advantage of reducing online computational time to enable real-time monitoring.

As can be seen from Fig. 9, the results have demonstrated both classical machine learning-based and deep learning-based unsupervised approaches with great potential in monitoring anomalies in WWTPs. Unsupervised classical machine learning algorithms (e.g., PCA-based, ICA-based, Manifold-based) are superior in automatically summarizing data features, extracting possible patterns, and exposing hidden data structures, and can achieve fast and sensitive anomaly detection in the absence of data labels. However, those classical machine learning approaches usually suffer from comparatively higher false alarm rates and lower fault detection rates with typically FAR exceeding 2.5 % and FDR below 95 %, largely due to their limitations in dealing with nonlinear and multimodal situations in wastewater treatment processes. In contrast, the corresponding unsupervised deep learning methods such as EBNN, DBN, RNN-RBM, PISAE, and M-VAE can provide higher detection accuracy and efficiency with reported improvements in FDR ranging from 3 to 12 percentage points and reductions in FAR to below 2 % in several studies. Although unsupervised learning does not require labelled data, it has additional needs in other aspects that involve model complexity and computational burden, real-time deployment, and model interpretation. In the coming work, strategies such as adaptive model updating, multi-model fusion, and parallel computation in distributed framework need to be developed to address these shortcomings and stimulate further advances.

3.2.3. Transfer learning and other AI-based models

Limited labelled data under varying operational conditions often prevent AI models trained for WWTPs' anomaly monitoring exclusively in a target domain from generalizing effectively. Because of this, several studies have considered to use transfer learning methods to take advantage of the knowledge from similar domains for fault diagnosis tasks. Table A.4 summarizes these transfer learning-related studies and their respective application points and performance metrics. The Enhanced Adaptive Sparse Bayesian Transfer Learning Machine (EAdspB-TLM) integrates TrAdaBoost-based instance weighting and Bayesian hyperparameter updating with the probabilistic relevance vector machine (PrRVM) model (H. Cheng et al., 2020). This approach reported that anomaly detection accuracy increased 13 %–35 % over traditional models, and was successfully used to detect aeration anomalies, ammonia nitrogen deviations, and nitrate concentration variances in WWTPs as well as in the Tennessee Eastman Chemical Process (TECP). M et al. (2023) and Sunal et al. (2024) proofed that pre-trained convolutional neural networks (CNNs) such as ResNet-50 and ResNet-34 can identify the presence of cavitation, bearing wear, or impeller damage in centrifugal pumps. These methods facilitated knowledge transfer from image datasets (e.g., ImageNet) into engineering signal images and recorded high classification accuracies up to 100 % (ResNet-50) and 85.98 % (ResNet-34), outperforming traditional handcrafted feature approaches by margins of 5–20 %. D. Yang et al. (2024) presented an unsupervised transfer learning method that combined Regularized Wasserstein Distance with Joint Distribution Adaptation (JDARWD). In experiments on alternative inflow conditions (dry, rain, and storm) on BSM1, the introduced model outperformed the baseline methods considerably, with the model's classification accuracy improved by 20.9 %–108.9 %.

Other AI related methods falling outside the category of supervised,

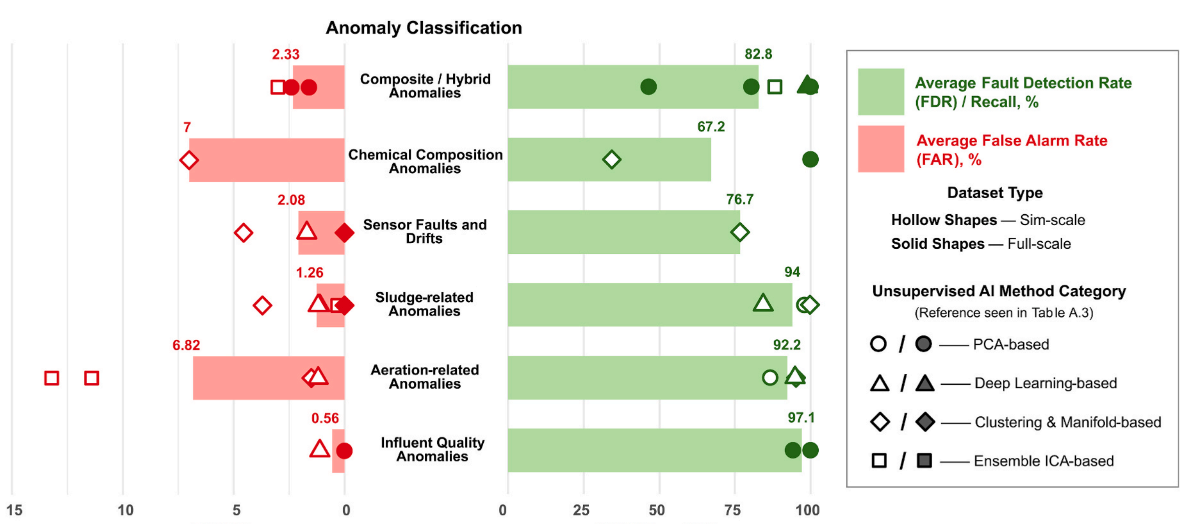

Fig. 9. FAR and FDR for unsupervised AI methods in wastewater treatment anomaly monitoring.

unsupervised, or transfer learning are also considered, such as particle filtering, Bayesian inference, hybrid optimization, and self/semi-supervised methods. As listed in Table A.4, these methods were successful in extracting nonlinear and dynamic characteristics of wastewater treatment processes. To deal with the complex nonlinear behaviour, self-supervised and semi-supervised models have been considered. H. Han et al. (2024) introduced the SMEL model, which combines stacked autoencoders and dual memory units for unsupervised anomaly detection. It achieved 97.1 % accuracy on the ST dataset and an F1-score of 92.4 % on the Yuqing River dataset, demonstrating strong generalization to nonlinear multi-source data. Under limited labelled data and multi-fault conditions, Ghinea et al. (2023) evaluated five semi-supervised models and found the convolutional autoencoder (Conv-AE) achieved the highest accuracy up to 98.64 % on the BSM2 datasets. For sensor drift faults, their system detected anomalies with a delay of only 3.84 h, highlighting its real-time capability. For robust state estimation in dynamic systems, Kenyeres and Abonyi (2023) proposed an intelligent particle filter (IPF) by integrating a genetic algorithm into the resampling step of the standard PF. Compared to traditional PF, the IPF improves estimation accuracy and enhances fault detection performance for bias and impact sensor faults, without increasing computational cost. Bayesian networks, as probabilistic graphical models, offer interpretable fault reasoning. Guo et al. (2016) developed a Bayesian network model using expert knowledge and historical data to support fault inference in WWTPs and handle uncertainty effectively in complex influent scenarios. Hybrid optimization-enhanced models have also gained attention. A fuzzy-chaos enhanced binary whale optimization algorithm (CF-BWOA) proposed by Anter et al. (2020) utilized fuzzy c-means clustering and chaotic initialization for feature selection and sensor fault classification. C.-L. Li et al. (2022) proposed the combination of the Mallat (MA) algorithm, weight-elimination (WE) algorithm, conjugate gradient (CG) algorithm, and multi-dimensional Taylor network (MTN) dynamic model (MA-WE-CG-MTN) to build residual-based fault indicators for lightweight deployment. Zhou et al. (2023) introduced the improved bald eagle search for KELM parameter tuning with kernel density estimation (IMBES-KELM-KDE). This model achieved 100 % FDR and 0 % FAR on sensor faults, much better than CNN, LSTM, and other baseline models in their research.

Currently, transfer learning and other AI models are mainly applied to cope with sparsely labelled data, nonlinear dynamics, and variable operational conditions in anomaly monitoring. Importantly, transfer learning exploits knowledge from similar domains to increase the generalizability of models and minimize dependence on labelled data. On the other hand, particle filtering, Bayesian inference, hybrid optimization, and self/semi-supervised techniques can offer flexibility, interpretability, and adaptability for real-time, multi-fault, and stochastic conditions. Hence, future studies should focus on the development of hybrid and integrated AI approaches to improve the robustness and usability for anomaly monitoring in real full-scale WWTPs.

3.3. Fault-tolerant control and resilience improvements

Fault-tolerant control and resilience enhancement technologies for WWTPs are designed to ensure stable operation and timely recovery from anomalies or suboptimal conditions. Due to the complexity and diversification of WWTPs, fixed parameter or semi-adaptive control methods are facing serious challenges. But AI-based methods with capabilities of adaptation, prediction, and intelligent decision support have been proven to be promising in enhancing fault tolerance and system resilience over the past few years. Fig. 10 summarizes the respective uses and relevant features of the methods validated either in simulation or real industrial environments. Recent studies in this field are centred on adaptive and self-healing control, soft sensor and fault-tolerant reconfiguration, predictive diagnosis and warning, and digital twins and virtual enhancement techniques. Fig. 10 divides the literature in this field into these four key topics and summarizes each topic from three aspects, including key features, application scenarios, and representative methods/models.

Recent studies on adaptive and self-healing control in WWTPs have focused on the employment of neural network-based models such as adaptive neuro-fuzzy inference systems (ANFIS), radial basis function neural networks (RBFNN), and broad learning systems (BLS). These approaches allow proactive adaptation as well as rapid post-fault

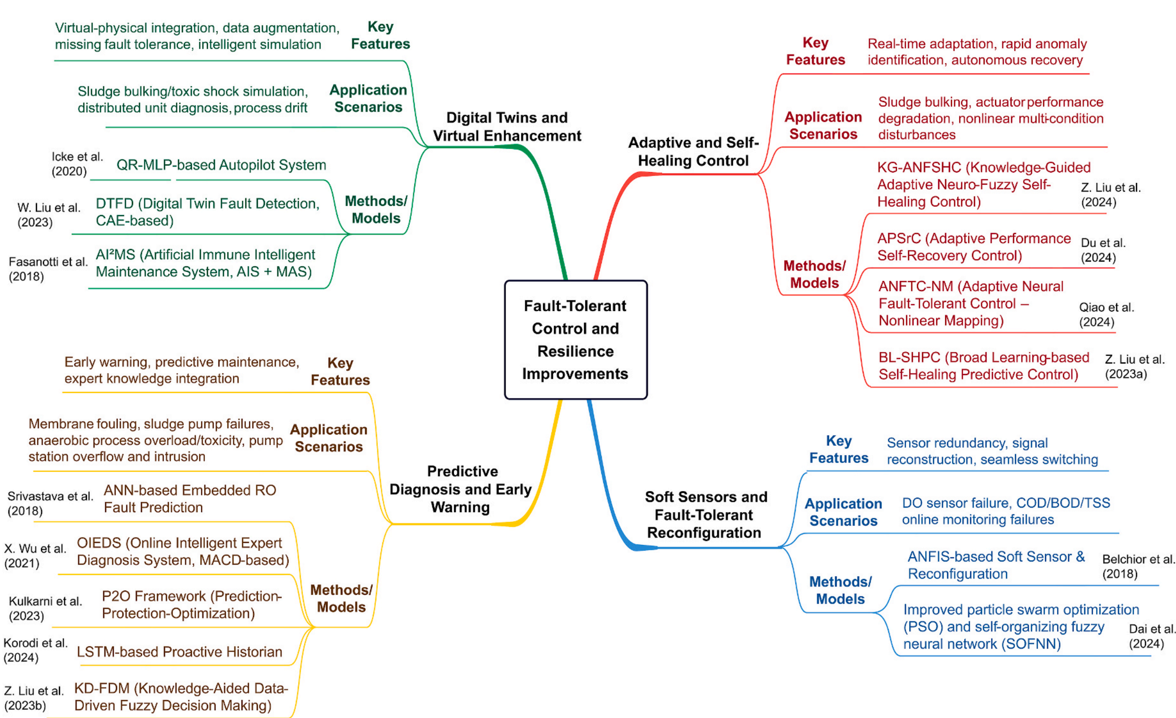

Fig. 10. Knowledge map of AI-based fault-tolerant control and resilience improvement methods in WWTPs.

recovery by automatically detecting anomalies and adjusting operational parameters in real time. For example, Z. Liu et al. (2024) introduced a knowledge-guided adaptive neuro-fuzzy self-healing control (KG-ANFSHC) strategy for sludge bulking mitigation. By tightly regulating DO and nitrate concentration, the scheme showed better accuracy and responsiveness on BSM2. Analogously, the Adaptive Performance Self-Recovery Control (APSrC) framework proposed by Du et al. (2024) controlled actuator faults effectively, and the Adaptive Neural Fault-Tolerant Control-Nonlinear Mapping (ANFTC-NM) strategy introduced by Qiao et al. (2024) was able to solve both actuator faults and actuator saturation. More importantly, BLS has now been adopted by Z. Liu et al. (2023a) to develop a broad learning based self-healing predictive control strategy (BL-SHPC), which increased resilience under sludge bulking conditions by quickly correcting anomalies and minimizing the need for manual intervention.

Soft sensors based on data-driven and fault-tolerant reconfiguration strategies are essential for provide process stability when sensor failures occur. For instance, ANFIS soft sensors have great potential in managing DO sensor faults and maintaining stable operations despite malfunctions in the sensor (Belchior et al., 2018). An improved particle swarm optimization (PSO) algorithm integrated with the self-organizing fuzzy neural network (SOFNN) can detect and classify sensor faults and process anomalies (e.g., sludge bulking and sensor drift), thereby giving WWTPs better abilities to respond rapidly as well as recover from such faults (Dai et al., 2024).

Machine learning predictive diagnosis and warning systems enhance WWTP resilience by fault anticipation and proactive intervention. Srivastava et al. (2018) employed artificial neural networks and embedded systems for fault prediction in reverse osmosis (RO) membranes to optimize maintenance. X. Wu et al. (2021) designed an intelligent online expert diagnosis system that used moving average convergence and divergence (MACD) indicators for anaerobic processes to rapidly identify and proactively intervene in toxic impacts and organic overloads. Further, Kulkarni et al. (2023) developed an AI-based Prediction-Protection-Optimization (P2O) framework that combined LSTM-based water level prediction, anomaly classification, and pump station optimization to manage overflow threats as well as sensor anomalies. Korodi et al. (2024) also proposed a decentralized proactive historian using LSTM networks for effective prediction of sludge pump malfunctions and influent quality anomalies. Additionally, Z. Liu et al. (2023b) developed a knowledge-aided data-driven fuzzy decision-making model (KD-FDM), which improved the accuracy of sludge bulking diagnosis and the timeliness of subsequent operational adjustments.

Digital twin technology is another effective tool to increase fault tolerance with the aid of virtual-physical integration. Icke et al. (2020) proposed a ML-based autopilot system utilizing quantile regression with multi-layer perceptron (QR-MLP) for the enhancement of operational stability and resilience under a range of disturbance conditions in a real WWTP. W. Liu et al. (2023) also developed a Digital Twin Fault Detection (DTFD) model based on convolutional autoencoders for real-time simulation and monitoring of sludge bulking and toxic impact faults. This model still performed well in anomaly detection accuracy as well as in false alarm rates with limited real-world fault information. Fasanotti et al. (2018) proposed an Artificial Immune Intelligent Maintenance System (AI^{2}MS), where artificial immune systems (AIS) and multi-agent systems (MAS) were integrated together to maximize fault detection, isolation, and recovery capabilities in distributed WWTP networks.

In short, intelligent decision-support systems based on mathematical modelling and residual analysis can effectively solve complex issues such as sludge bulking and process instability in WWTPs and show better interpretability and faster anomaly detection (W. Liu et al., 2023; Z. Liu et al., 2023c; X. Wu et al., 2021). By coupling multi-source data fusion with advanced modelling methods, the above AI-based techniques have transformed the passive control mode into a proactive, knowledge-driven management framework, which can improve the system's robustness, operational efficiency, and decision-making autonomy.

3.4. Challenges, limitations, and future trends

Development and application of AI-based approaches for managing anomalies in WWTPs face various challenges and limitations. The first challenge involves data quality and reliability. Maloperation and fouling of sensors, calibration drift, and noise disturbance can deteriorate the data stream and lead to distorted or lost inputs (Ba-Alawi et al., 2023a). If AI-driven systems are trained on these abnormal datasets, their reliability can be undermined due to defective anomaly detection or diagnosis. Cross-facility variation brings another significant challenge. Since the operating conditions and influent characteristics in different WWTPs vary, AI models that perform well for one facility may work poorly if applied to another due to changes in data distributions and process dynamics (D. Yang et al., 2024b). Most existing models are not yet adaptable enough to transfer knowledge among the WWTPs. This facility variability and overall data integrity issues, indicate the necessity of more powerful and more adaptive AI solutions for the application.

Apart from these challenges, the current AI strategies also exhibit several intrinsic limitations, which present practical application inefficiencies. The first major limitation concerns the transparency and interpretability of those state-of-the-art models. Complex deep learning algorithms can act as "black boxes" making it difficult for on-site operators to comprehend and trust AI-generated alarms or diagnostic results when making operational decisions (Ba-Alawi et al., 2023b). Second, the limited ability of AI-based methods for real-time processing at large scale due to the high computational demand is another constraint. Models such as transformers or VAEs possess tremendous power, but computational complexity prevents their application in real-time under resource-scarce conditions (Peng et al., 2022b). These kinds of models that run well in the lab may struggle to meet the online feedback speed requirements of WWTP monitoring and control. Furthermore, the cost of deploying AI-driven anomaly management systems at an industrial scale is uncertain. While positive influence can be inferred from early research findings, the additional costs associated with sensors, data infrastructure, model training, and maintenance are not yet well quantified (Ba-Alawi et al., 2021; Cassidy et al., 2020). With all these limitations, water utilities may currently be reluctant to take the risk of investing in or adopting AI-based anomaly management solutions at full scale in WWTPs.

Future innovations will be helpful in overcoming these challenges and limitations. Improving sensor data should be of primary importance, which can be achieved by the integration of real-time data quality assessment and adaptive signal processing modules into Supervisory Control and Data Acquisition (SCADA) systems. Accordingly, developing resilient preprocessing and automated self-calibration techniques will help ensure AI algorithms operate on accurate, high-quality inputs. Advanced multi-sensor data fusion and outlier detection methods can also be employed to filter noise and correct sensor drift in real time, preventing "garbage-in", "garbage-out" situations. Another critical direction will be the improvement of model generalizability across facilities. The collaborative AI model training across multiple sites can be achieved based on the information from multiple WWTPs. Transfer learning, domain adaptation, and federated learning can be used to transfer knowledge from plant to plant. Adaptive learning strategies should also be sought so that the model can update or recalibrate promptly as new data arrives. AI-based systems can adapt to varied influent patterns and anomaly types by means of online learning or incremental models to perform well under different conditions. Furthermore, generative adversarial networks (GANs) demonstrate a new way of generating additional anomaly samples, which can be employed for extending the size of the training datasets as well as the capability of the model to interpret previously unrecognized types of faults (Xia et al., 2022). GAN-based data augmentation can enhance adaptive learning frameworks, especially in cases where labelled anomaly data is limited. Explainability and large-scale deployment of AI solutions should be among other future research priorities. Attention-based models excel at capturing complex dependencies and salient features in multivariate time series, which may enhance early detection and interpretation of process anomalies (Niu et al., 2021). Future studies are encouraged to investigate the adaptation and implementation of these techniques within the WWTP context, as data availability and computational capabilities continue to advance. Incorporating explainable tools (e.g., SHapley Additive exPlanations (SHAP) or Local Interpretable Model-agnostic Explanations (LIME)) into AI-based anomaly detection and diagnosis models or operational systems will be one of the potential ways to reduce the "black box" nature of AI models (Ravi et al., 2021; Zou and Petrosian, 2020). It should be noted that while explainable or interpretable AI methods can provide valuable insights into model behaviour and support validation with existing domain knowledge, they do not directly reveal real-world mechanistic or causal relationships (Antwarg et al., 2019; Ravi et al., 2021). Instead, such measures are appropriate ways of assessing model consistency with expertise and generating hypotheses for future research, but they do not provide causally explanatory results. Integration of AI models with digital twin platforms is also a promising direction. A digital twin is a virtual visualization of the treatment plant, so coupling AI with such simulations allows for the safe testing of anomaly scenarios and control strategies in a risk-free environment. Through computer simulation experiments, researchers can generate worthwhile results employing the synthetic data of rare events in order to improve fault detection algorithms and resilience strategies before they can be used in real systems. To meet real-time operational requirements, the design of lightweight AI architecture and the use of edge computing are also research directions that deserve more attention. Future studies should pay more attention to model compression, the design of lightweight neural networks, and distributed computation frameworks, since these methods can reduce hardware load and inference latency without losing accuracy. Finally, the practicality of AI-based anomaly management systems should be determined through cost–benefit analyses along with industrial pilots. Quantifying the trade-offs between performance improvements (e.g. fewer effluent violations, energy savings, and environmental protection) and the implementation costs will help demonstrate a clear commercial landscape. If these paths are followed, future research can fill the noteworthy gaps we have highlighted in the survey. These multi-faceted efforts will be of great benefit in the evolution of more resilient, transparent, and cost-effective AI uses for anomaly management of WWTPs.

4. Conclusions

This work critically reviewed the theoretical development and industrial application of AI across the life cycle of anomaly management in WWTPs, identifying important opportunities and current limitations. Findings revealed that AI-based approaches significantly improved the management of sensor data quality and self-calibration, thus providing robust support for downstream anomaly detection and diagnosis. Different AI approaches and tools exhibited varied and specialized developments in anomaly detection and fault diagnosis, well responding to the multimodal, highly noisy nature of wastewater treatment processes and enabling real-time, accurate monitoring and decision-making. Concurrently, the important contribution of AI approaches to fault-tolerant control and improvement of system resilience was also highlighted, where adaptive learning and intelligent decision-support significantly improved the speed of system recovery in the face of complex disturbances. However, the implementation of AI technologies faces various critical constraints. Data quality remains a major challenge, where the drift and failure of sensors induce data distortions that can compromise model accuracy and reliability. Generalizability of AI across different WWTPs was another big issue, considering the diversity in operating conditions and influent properties across facilities. Lack of interpretability by AI models also limited their adoption and trust in real-world applications. The high computational demands of complex AI algorithms also came in conflict with the real-time monitoring requirements of WWTPs. For the future, research ought to focus on the use of hybridised data fusion, lightweight and real-time model architectures, transparency through explainable AI approaches, and more flexible transfer learning frameworks. Overcoming these constraints is expected to enable generalised, responsive, cost-effective intelligent anomaly management systems, thus improving the sustainability and operational efficiency of the wastewater treatment industry in real-world operations.

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CRediT authorship contribution statement

Sen Yang: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. **Kourosh Behzadian:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Chiara Coleman:** Writing – review & editing. **Timothy G. Holloway:** Writing – review & editing, Supervision. **Luiza C. Campos:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2025.126886.

Data availability

Data will be made available on request.

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