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Review

AI-driven solutions in wastewater treatment and agricultural reuse systems: A comprehensive review

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ABSTRACT

Wastewater reuse for irrigation is a key solution to freshwater shortages and food crises caused by population growth and climate change, aligning with circular economy and sustainable development principles. However, traditional techniques struggle to handle the complex nonlinearities in wastewater reuse, which hinders broader adoption. Artificial intelligence (AI) can effectively capture and manage the complex dynamics in wastewater treatment and irrigation—two crucial stages in wastewater reuse—making it a promising technology for future development. This review aims to critically examine the application of AI in both wastewater treatment and agricultural reuse, highlighting technical limitations, regulatory misalignments, and implementation gaps. Studies show that AI enhances wastewater treatment by improving real-time water quality monitoring, effluent quality, energy savings, and cost reduction. AI also optimizes irrigation by improving water reuse efficiency, scheduling, and reducing risks like over-irrigation and soil contamination, boosting agricultural productivity and sustainability. However, existing AI models are primarily designed based on wastewater discharge standards, overlooking reclaimed water requirements. A notable example of this misalignment is the persistent focus of AI models on specific pollutants removal (e.g., nitrogen), aligned with traditional discharge standards, despite these pollutants no longer being key parameters under reclaimed water quality criteria (e.g., Regulation (EU) 2020/741). AI models also focus heavily on predicting conventional water quality parameters while neglecting contaminants of emerging concern (CECs). Moreover, many AI models are only validated in simulated environments and do not provide robust evidence of performance in real-world reuse systems. The review concludes with a roadmap of future research needs, offering practical insights for researchers, plant operators, and policymakers. This synthesis serves as a reference framework to guide the development of integrated, quality-aware AI systems for sustainable water reuse.

Abbreviations: AI, Artificial intelligence; AAO, Anaerobic-Anoxic-Oxic; ABAC, Ammonia-based aeration control; ANN, artificial neural network; ARGs, antibiotic resistance genes; BOD_5, Biochemical Oxygen Demand over 5 days; BPNN, Backpropagation Neural Network; CECs, contaminants of emerging concern; CNN, convolutional neural network; CSS, collision cross-sections; CWs, Constructed wetlands; DO, Dissolved Oxygen; DNN, deep neural network; DT, decision tree; EQI, water quality standard parameters; FBPNN, Feedforward Backpropagation Neural Network; FL, fuzzy logic; GA, genetic algorithm; GEP, Gene Expression Programming; HPLC-MS/MS, High-Performance Liquid Chromatography-Tandem Mass Spectrometry; HANs, haloacetonitriles; IoT, Internet of Things; K-NN, K-nearest neighbor; LSTM, long short-term memory; MLSS, Mixed Liquor Suspended Solids; MPC, Model Predictive Control; MOALO, multi-objective ant lion optimization; NBS, Nature-Based Solutions; NH_3-N, Ammonia Nitrogen; NO_3-N, Nitrate Nitrogen; ORP, Oxidation-Reduction Potential; PCA, Principal Component Analysis; PAA, peracetic acid; PPCPs, pharmaceuticals and personal care products; PID, Proportional-Integral-Derivative; PSO, Particle swarm optimization; qPCR, Quantitative Polymerase Chain Reaction; RF, random forest; RNN, recurrent neural network; RT, retention time; SHAP, SHapley Additive exPlanations; SMX, Sulfamethoxazole; SS, Suspended Solids; SVM, support vector machine; SVR, Support Vector Regression; TN, Total Nitrogen; TKN, Total Kjeldahl Nitrogen; TP, Total Phosphorus; THMs, trihalomethanes; UV, ultraviolet light; WWTPs, wastewater treatment plants.

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1. Introduction

Due to the impact of population growth and extreme weather, the world is facing a considerable food crisis (Wheeler and von Braun, 2013; Liu et al., 2023a). Currently, over 250 million people are suffering from severe hunger, a situation that is expected to worsen in the future (FSIN, 2023; Xu et al., 2023). Agricultural activities are essential for sustaining the global population and alleviating this problem. Although food production has already increased by more than 100 % in the last 30 years, the Food and Agriculture Organization of the United Nations (FAO) estimates that by 2050, about 50 % more food will be needed to meet the food requirements of a growing global population with changing dietary patterns (FAO, 2024). Approximately 70 % of the world's freshwater resources are used for agricultural irrigation (Food, 2023; Radini et al., 2023). Water and food are closely linked; about 40 % of global agricultural production derives from irrigated land, which is only about 20 % of all agricultural land (FAO/OECD, 2021). However, it is disheartening that global natural water resources are also facing severe shortages (Rockström et al., 2023; Nature, 2023). Reports indicate that a significant number of rivers worldwide are on the path to depletion (Foglia et al., 2023). In the future, natural water resources for agricultural irrigation may become an unaffordable luxury. Therefore, finding alternative water sources to natural freshwater has become one of the primary solutions to address the current water and food crises and to promote global sustainable development (Scanlon et al., 2023). The use of reclaimed water has become an important option for alleviating water shortages and for use in agricultural irrigation (Foglia et al., 2021; Harris-Lovett, 2024). AI-driven solutions" as computational approaches, based on machine learning, data mining, or expert systems, that enhance or automate monitoring, prediction, and control processes in both wastewater treatment and agricultural irrigation. This review is structured around the central research question: *In what ways can AI improve the efficiency, safety, and sustainability of water reuse for agriculture?* It is estimated that urban wastewater worldwide can generate over 3.5×10^{11} m^3 of wastewater annually, which accounts for approximately one-third of the freshwater used for irrigation from surface and groundwater sources (Pikaar et al., 2022; Jones et al., 2021; Rosa et al., 2020). Additionally, compared to natural water sources, wastewater contains more nutrients (including nitrogen, phosphorus, potassium, etc.), which can effectively enhance soil fertility, promote plant growth, and reduce the need for chemical fertilizers (Ofori et al., 2021; Ricart and Rico, 2019; Odone et al., 2024). Therefore, in the context of the current water and food crises and the development of circular economy, wastewater can be regarded as a resource rather than a waste, and it is currently applied for agricultural irrigation in different areas of the world (Chen et al., 2021; Voulvoulis, 2018; Yadav et al., 2021). However, if not properly treated, and due to its complex composition and the potential presence of various contaminants, reclaimed water may pose ecological risks to the environment, such as altering the physicochemical properties and microbial characteristics of the soil (Khan et al., 2022; Lyu et al., 2022). Additionally, its cost remains significantly higher than that of natural water sources used for irrigation, making its further adoption challenging (Salminen et al., 2022; Verlicchi et al., 2023). Therefore, it is important to estimate in a precise way concentration of different substances in reclaimed water in the case of agricultural reuse.

Wastewater treatment systems (e.g., Wastewater Treatment Plants (WWTPs) and Nature-Based Solutions (NBS)) are crucial components of agricultural water reuse systems, playing a key role in the purification and production of reclaimed water for agricultural use (Christou et al., 2017; Zhang et al., 2021; Nan et al., 2020). Improving the efficiency of this stage is crucial for ensuring the water quality of reclaimed water, reducing production and usage costs, and expanding its application in agriculture (Mannina et al., 2022). However, traditional models and techniques based on physical methods and human experience cannot effectively handle the complex mechanisms of these processes, particularly in WWTPs with microbial treatment processes. This significantly hampers effective water quality purification and cost reduction (Alvi et al., 2023; Singh et al., 2023). Therefore, there is an urgent need to seek advanced technologies to transform the traditional operation modes of wastewater treatment systems to further ensure reclaimed water quality and reduce cost.

AI, as one of the most advanced technologies in contemporary civilization, has garnered unparalleled attention in recent years (Wu et al., 2020; Jan et al., 2023; Tomasev et al., 2020). AI is now widely applied across various sectors, including the environment, economy, healthcare, and information technology, since it can process vast amounts of data to learn patterns, trends, and rules (Li et al., 2023; Moor et al., 2023; Scheffler et al., 2022; LeCun et al., 2015; Dwivedi et al., 2021). This data-driven approach allows AI to learn from experience and make more accurate predictions and inferences in new scenarios, as well as to handle complex mechanisms and nonlinear characteristics (Hase et al., 2020; Tzachor et al., 2023; Sapoval et al., 2022). In recent years, AI has also found significant applications in wastewater treatment (Zhao et al., 2020; Iratni and Chang, 2019). AI technologies can enhance the performance of wastewater treatment systems by improving tasks such as water quality monitoring, intelligent control, and fault diagnosis. This leads to more efficient pollutant removal and ensures water quality safety, while also reducing operational energy consumption and cost (Alvi et al., 2023; Alam et al., 2022; Liu et al., 2023b). However, several recent studies have addressed the role of AI in either wastewater treatment (Liu et al., 2023b; Yang and Li, 2025; Baarimah et al., 2024) or agricultural irrigation (Anil Chougule and Mashalkar, 2022). Nevertheless, these studies often treat the two domains in isolation, overlooking the complex feedback loops between reclaimed water production and its reuse in precision agriculture.

This review addresses this critical gap by systematically analyzing AI applications across both domains, focusing on reclaimed water quality, real-time monitoring, reuse-specific control objectives, and socio-technical challenges. In Section 2, the methodology adopted for this review is detailed, highlighting the systematic selection process of relevant scientific studies. Section 3 elucidates the specific connotations, advantages, and disadvantages of AI technologies, and summarizes common AI models. Section 4 summarizes the applications of AI technologies in wastewater treatment, highlighting the shortcomings of AI applications in the context of wastewater reuse. Section 5 explores the role of AI in agricultural irrigation, discussing how AI technologies optimize reclaimed water reuse, enhance irrigation efficiency, and promote sustainable agricultural practices. Section 6 outlines the challenges and prospects of AI technologies in wastewater reuse and offers recommendations for future research and technological advancements. Finally, in Section 7 the paper concludes by summarizing and reviewing the key points discussed throughout the text. Thus, this review provides comprehensive information for a deeper understanding of AI applications in wastewater treatment and reuse, promoting technological upgrades in key aspects of reclaimed water reuse through AI.

2. Methodology

As a first step to deeply analysing the review's topic the authors selected "Artificial Intelligence", "Agriculture", "Water", "Wastewater Treatment", "Agricultural irrigation" as the most research-representative keywords. These keywords constitute the total of those used within the study; the search strings were based on the combination of those different keywords, considering the most relevant to the section topics as detailed in Table 1. The keywords were carefully chosen to encompass a broad spectrum of relevant papers for comprehensive coverage. The selected keywords were queried in the Web of Science (WoS) database, renowned for its high scientific impact and considered one of the most comprehensive repositories of peer-reviewed journals, widely used in high-impact environmental and engineering review articles (Zhang et al., 2023a; Li et al., 2024a; Yu et al., 2024). In detail, for

Table 1
– Used keywords for the search in the WoS database.

Section	Addressed topics	String used in WoS for the search
3)	AI technologies in agricultural water	((TI = "Artificial Intelligence" OR AB = "Artificial Intelligence" OR AK = "Artificial Intelligence") AND (TI = "Water" OR AB = "Water" OR AK = "Water") AND (TI = "Agriculture" OR AB = "Agriculture" OR AK = "Agriculture"))
4)	AI and wastewater treatment	((TI = "Artificial Intelligence" OR AB = "Artificial Intelligence" OR AK = "Artificial Intelligence") AND (TI = "Wastewater treatment" OR AB = "Wastewater treatment" OR AK = "Wastewater treatment"))
5)	AI and agricultural irrigation	((TI = "Artificial Intelligence" OR AB = "Artificial Intelligence" OR AK = "Artificial Intelligence") AND (TI = "Agricultural irrigation" OR AB = "Agricultural irrigation" OR AK = "Agricultural irrigation"))

each specific section, the selected keywords were systematically queried in the WoS database using the Title/Abstract/Keywords search domain.

The selection of scientific articles to be included in each section of the review was conducted through a defined 4-phase process (from A to D). In phase A, for each section, individual strings, as listed in Table 1, were used for the articles search in the WoS database using the Title/Abstract/Keywords search domain, taking note of the total number of studies published in the literature up to the date of the search. For all the sections, an overall of 912 studies were identified (Fig. 1 (Phase A)). In phase B, only review and research articles published within the 10-year period from 2014 to 2024 were counted in order to capture recent advancements within the designated timeframe. This approach aimed to ensure that the review encompassed the most pertinent scientific works within the designated timeframe. Fig. 1 (Phase B) shows the total number of studies (757) distributed for each section on yearly basis. In phase C, the studies identified in the previous phase B underwent preliminary screening at the abstract level to evaluate their relevance to the addressed topics and their consistency with the review's objectives. In phase C, each study was categorized into one of three key sections: Section 3 - focusing on the relationship between AI and water management in agriculture; Section 4 - emphasizing the role of AI in processes such as water quality monitoring, intelligent control systems, fault diagnosis, and specialized applications in tertiary treatment technologies; Section 5 - addressing how AI technologies optimize the use of reclaimed water in irrigation, enhance water use efficiency, and promote sustainable agricultural practices. Fig. 1 (Phase C) shows that the total number of selected studies was 301. In phase D, for the studies identified in the previous phase C, the related full texts were acquired and thoroughly reviewed for their relevance within the aims of this review. Subsequently, after full-text analysis, as depicted in Fig. 1 (Phase D), 120 studies were selected as the ones that fulfilled the topic, while the others were excluded due to their lack of relevance to the review's topic. In detail, studies were selected for final inclusion only if they met the following criteria: (i) they explicitly addressed the application of AI in the context of wastewater treatment systems, whether based on conventional technologies or NBS systems; and (ii) they clearly framed their objective within the context of producing treated water for agricultural reuse, specifically for irrigation purposes.

The description reported above provides a comprehensive understanding of the selection methodology and the rationale behind the inclusion of studies in both qualitative and quantitative synthesis. It outlines the detailed process of identification, screening, and eligibility criteria used to select relevant studies, specifying the inclusion and exclusion criteria applied (e.g., domain, time frame, article type, etc.) for each investigated topic. Additionally, it details the number of studies initially identified, screened, and ultimately included in the review.

3. AI technologies

The concept of AI was first introduced by John McCarthy at the Dartmouth Conference in 1956, which is considered the inception of AI research. After 1980, AI experienced rapid development following the introduction of various AI models (also known as machine learning (ML) models). In the past decade, the advancements in deep neural networks and GPUs have once again propelled AI into various fields, marking a period of significant AI proliferation (Pichler and Hartig, 2023; Wang et al., 2023a). Although there is no universally accepted definition of AI, current research typically views AI technologies as a broad concept encompassing big data, ML, computer vision, and more (Vinuesa et al., 2020; Kaspar et al., 2021). Regardless of the field or scenario, models are at the core of AI technology applications. Research on AI in wastewater treatment also primarily revolves around AI models (Iratni and Chang, 2019; Niu et al., 2022a). As shown in Fig. 2, commonly used AI models include artificial neural network (ANN), support vector machine (SVM), fuzzy logic (FL), genetic algorithm (GA), decision tree (DT), and random forest (RF), etc. (Alam et al., 2022; Bahramian et al., 2023). Among these, neural networks are the most widely used in water resources domain due to their excellent fault tolerance and robustness in handling nonlinear problems. Besides the basic standalone models mentioned above, AI models are often used in combination, such as GA-ANN, PSO-ANN, and FL-ANN (ANFIS) (Alam et al., 2022). Generally, compared to single models, hybrid models tend to achieve better performance, although this may increase model complexity and computational costs.

Although traditional mathematical models have made significant contributions to scientific research and modern industrial systems, they still face application obstacles due to the discrepancies between ideal assumptions and the complexities of real-world environments. For example, in membrane technologies commonly used in wastewater treatment and reuse systems, the complexity of wastewater environments hinders the practical application of membrane fouling analysis and prediction models under ideal conditions, as single membrane fouling blocking formulas struggle to fit the membrane fouling processes throughout the entire filtration cycle (Niu et al., 2022a; Viet et al., 2021; Safeer et al., 2022). In contrast, AI models do not rely on inherent physical formulas and human experience, and they can avoid errors based on assumptions under ideal conditions, making them more suitable for application in complex real-world environments, including wastewater treatment and agricultural reuse. For example, ANN in AI models can effectively predict the concentration of target pollutants in effluent based on parameters such as initial concentration of target pollutants, contact time and pH in influent water (Ye et al., 2020).

In terms of AI model limitations, AI models, particularly deep learning models, are often regarded as "black boxes," making it difficult to explain their decision-making processes in real-world applications (Pichler and Hartig, 2023; Ryo et al., 2020; Wein et al., 2021). This is a disadvantage in the context of reclaimed water quality monitoring and safety assessments, as operators and regulatory agencies often need to clearly understand every step of the treatment process. Notably, most AI models are trained under specific conditions and lack cross-scenario generalizability. However, real-world wastewater treatment for reuse involves highly variable conditions, such as seasonal changes in water composition and regional differences. This necessitates that future AI models possess strong adaptability and flexibility to accommodate these variations. Additionally, the performance of artificial intelligence models largely depends on the quality and quantity of data. If training data contains biases, noise, or incompleteness, the model's performance will be significantly affected. This is especially common in the modelling process of wastewater treatment, where data missingness and noise are prevalent phenomena (Nourani et al., 2021). Developing more efficient AI models specifically for wastewater treatment scenarios to handle large-scale and complex datasets is an effective way to improve model performance (Nourani et al., 2021; Ma et al., 2020; Wang et al., 2024a).

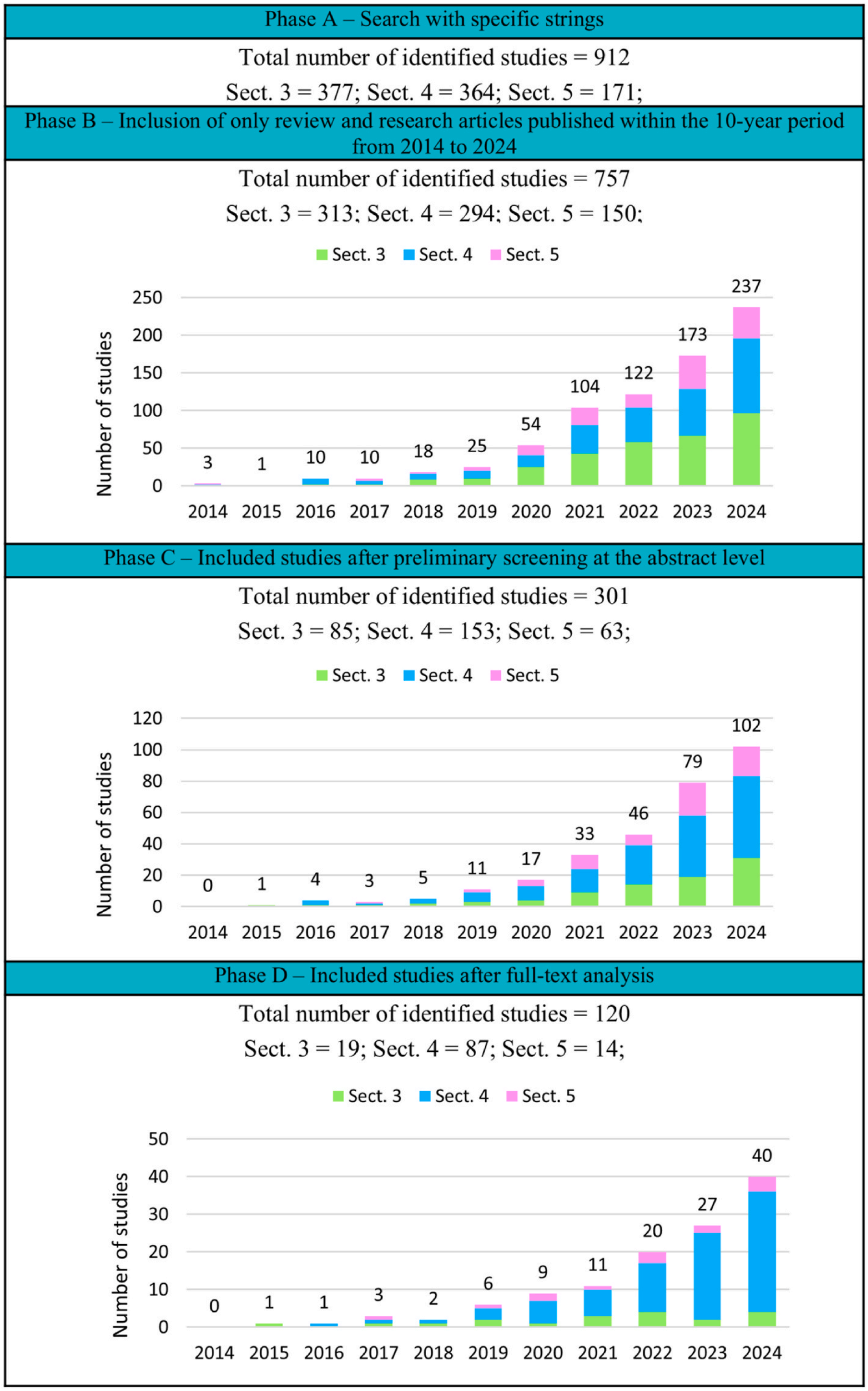

Fig. 1. Search methodology: number of studies during the 4-phase (from A to D) selection process.

4. Role of AI in wastewater treatment

Wastewater treatment is a crucial step for the reuse of reclaimed water. Ensuring water quality and reducing costs are key to promoting wastewater reuse. This chapter will discuss how AI technology can help overcome technical limitations, reduce costs, and advance wastewater treatment and reuse. The specific content covers water quality monitoring, intelligent control, fault diagnosis, and the role of AI in tertiary treatment technologies (Fig. 3).

4.1. *Water quality monitoring*

Water quality monitoring is a crucial tool for understanding variations in the performance of WWTPs. It is essential for adjusting the wastewater treatment process and determining whether the effluent is suitable for discharge or reuse. However, traditional models and detection methods face technical challenges, such as dynamic water quality disturbances, high nonlinearity in biochemical processes, and delays in testing certain specific indicators (Bekkari and Zeddouri, 2019; Gao et al., 2023a). AI-based water quality monitoring provides effective

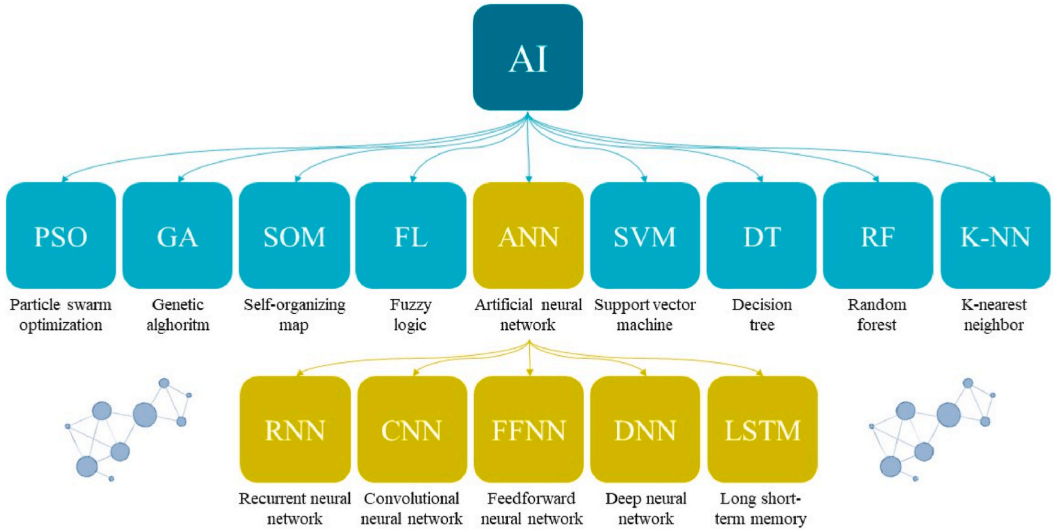

Fig. 2. Common AI technologies and models.

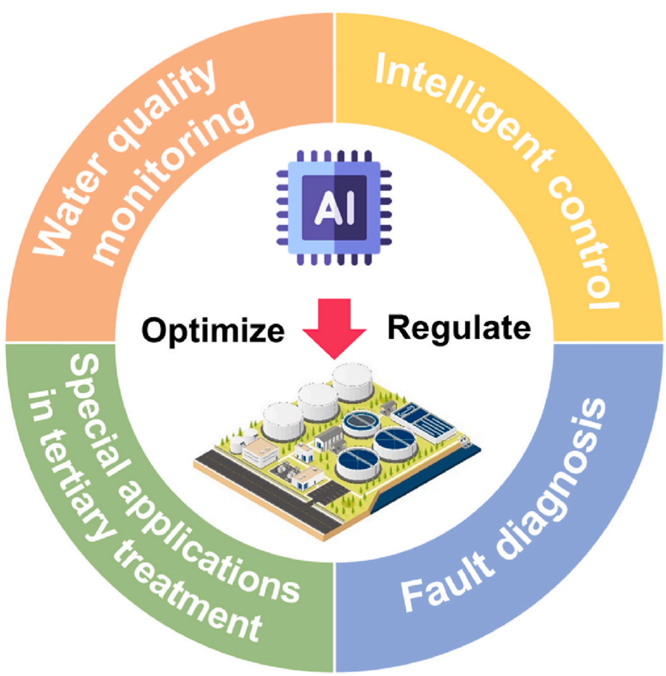

Fig. 3. Applications of AI in wastewater treatment.

technical support to overcome these challenges. The application of AI in water quality monitoring mainly focuses on water quality prediction and soft sensing (Bekkari and Zeddouri, 2019; Aghdam et al., 2023; Li et al., 2024b). Water quality prediction uses modelling methods to monitor the unpredictable effluent quality in wastewater treatment, which is processual and temporal. Soft sensing utilizes easily measurable variables (usually measured online via sensors) to monitor water quality variables that are difficult to measure directly or take too long to measure. Importantly, two parallel tracks of AI development regarding CECs must be distinguished. On one side, AI models, especially ANNs and SVMs, are increasingly employed to aid the detection and classification of CECs in complex analytical datasets, such as HRMS outputs (Hollender et al., 2019). These tools support the prediction of retention times (RT) and collision cross-sections (CCS), improving identification confidence for pharmaceuticals and personal care products (PPCPs) in environmental samples. For instance, Song et al. (2024) demonstrated that machine learning models can accurately predict RT values for hundreds of known and unknown CECs, drastically reducing the time and uncertainty in HRMS-based workflows. However, these advances are largely confined to laboratory settings. In contrast, the application of AI for real-time CECs monitoring and dynamic control at the WWTP level, e.g., integrating soft sensors to regulate aeration or chemical dosing based on predicted CECs concentrations, is still in its initial stage. Bridging this lab-to-plant gap remains a pivotal challenge in the development of next-generation reclaimed water safety systems. Despite their differences, both enhance the real-time monitoring capability of WWTPs, providing real-time data support for optimizing and adjusting the wastewater treatment process.

In terms of feature selection for model inputs, studies related to water quality prediction typically select influent water quality parameters (pH, temperature, DO, COD, TN, etc.) and gas phase factors (humidity, etc.) as input features (Table 2). Some studies choose a more extensive and complex range of input features, including process parameters at various stages of water treatment (Xie et al., 2024; Lv et al., 2024). For soft sensing, the selected input features often differ from the target output variables. Easily measurable water quality indicators and gas phase conditions are commonly chosen in soft sensing (Aghdam et al., 2023; Zhang et al., 2023b). Due to the complexity of the wastewater environment, many indicators may correlate with the treatment process, which is why numerous indicators can be selected as input features for models in the wastewater treatment process (Xie et al., 2024; Khatri et al., 2020). However, more features do not necessarily lead to better performance. For example, researchers have used SHAP analysis to remove low-contribution features, significantly reducing the cost of model construction and inference without considerable loss of accuracy (Zhang et al., 2023b). In terms of model type selection, although many models can perform water quality prediction and soft sensing tasks, choosing the appropriate model for a specific task theoretically yields better performance. For instance, compared to traditional ANN models, LSTM's memory units, gating mechanisms, and end-to-end learning capabilities allow it to handle time series data more effectively, capturing temporal correlations and making it more suitable for water quality prediction tasks (Yang et al., 2023; Yaqub et al., 2020). Additionally, DNNs, with their multiple nonlinear processing units, can effectively capture complex patterns and relationships in wastewater, often achieving higher predictive accuracy compared to other AI models (Alvi et al., 2023). Recently, they have been widely applied in water quality monitoring studies (Alvi et al., 2023; Xie et al., 2024).

Also in the case of NBS applications, several AI-driven models (ANN

Table 2
Research on water quality monitoring.

Scenario	Modle Type	Inputs	Outputs	Performance	Key Finding/Limitation	Ref.
Predict						
Touggourt WWTP	FBPNN	Influent: pH, temperature, SS, TKN, BOD, COD	Effluent: COD	R = 0.87	Moderate accuracy; limited to a small influent dataset and single effluent target.	Bekkari and Zeddouri (2019)
Yong-yeon WWTP	ANN	Influent: Month, flow rate, pH, temperature, COD, SS, TN	Effluent: TN	$R^2 = 0.47$	Low predictive power; suggests model underperformance due to temporal variability and limited input resolution.	Guo et al. (2015)
Tabriz WWTP	SVR (SVM)	Influent: BOD, COD, SS, pH etc.	Effluent: BOD, COD	RMSE = 0.0155	High accuracy; model benefits from balanced influent parameters but lacks CECs consideration.	Nourani et al. (2021)
Jiangsu WWTP	TCN-LSTM (DNN)	Influent and process: Inflow rate, COD, ammonia nitrogen, TN, TP, pH, DO, ORP, etc. (33 parameters)	Effluent: TN	$R^2 = 0.855$	Strong performance on time-series data; highly complex model architecture may hinder transferability.	Xie et al. (2024)
Henan WWTP	BPNN	Influent and process: Flow rate, COD, TN, biochemical tank COD, biochemical tank TN, temperature, humidity, etc. (10 parameters)	Effluent: TN, NO_3	$R^2 = 0.9743$ (TN) $R^2 = 0.9938$ (NO3-N)	Excellent fit; focused on key process variables, but dataset context and generalization not discussed.	Lv et al. (2024)
Okcheon WWTP	LSTM	Influent: TOC, NH_3-N, TN, TP, COD, SS, DO, ORP,	Removal efficiency: NH_3-N, TN, TP	MSE = 0.0047 (NH_3-N), 0.015 (TN), 0.018 (TP)	Robust performance with temporal inputs; not validated under reuse-quality standards or diverse WWTPs.	Yaqub et al. (2020)
Membrane System	ANN	Influent: Solution concentration, SMX concentration, pH, and natural organic matter	Removal efficiency: SMX	$R^2 = 0.987$	High accuracy in lab-scale setting; model lacks generalizability to field-scale systems.	Nam et al. (2023)
Constructed Wetlands	AutoML	Influent: pH, temperature, temperature, conductivity, dissolved oxygen, ORP, antibiotic, etc. (12 parameters)	Removal efficiency: antibiotic	$R^2 = 0.877$	Promising for non-conventional systems, but dependent on limited training data	Bao et al. (2023)
Soft sensing						
7 WWTPs in Hong Kong	GEP (GA)	TSS, Organic N, NH3-N, Inorganic P, Organic P	COD, BOD_5	$R^2 = 0.861$ (COD), 0.784 (BOD_5)	Multi-site applicability; missing real-time input handling; black-box interpretation limits usability.	Aghdam et al. (2023)
Shenzhen WWTP	LSTM (DNN)	pH, NH_3-N, SS, temperature, conductivity, Turbidity, DO, air pressure, precipitation, humidity, wind speed, visibility	COD, TN, TP	$R^2 = 0.9141$ (COD), 0.9239 (TN), 0.9040 (TP)	Strong accuracy, but requires large, high-quality multivariate dataset	Zhang et al. (2023b)
Textile desizing wastewater	GA-RF	Sample spectral curve	COD	$R^2 = 0.97$	High performance in specific industrial wastewater; single-indicator output limits wider applicability.	Huang et al. (2023)
New York State Port	DNN	DO, temperature, salinity, pH, ammonia, etc. (26 parameters)	BOD_5	$R^2 = 0.9310$	Strong predictive capacity across dynamic conditions; limited interpretability and model transparency.	Ma et al. (2020)

model) helped to analyze large datasets related to pollutants (e.g., PFAS) transport and removal, predict pollutant (e.g., PFAS) removal efficiency under different conditions, optimize the design and operation of these treatment systems (e.g., constructed wetlands) (Savvidou et al., 2024). Moreover, it was found that the AutoML models provide more reliable and precise predictions of how antibiotics are removed in CWs under varying conditions. For example, researcher used the AutoML models to optimize CW design and operation for antibiotic removal. The model suggested optimal conditions for maximizing removal efficiency, such as adjusting flow rates, selecting appropriate plant species, and managing wetland configuration. However, a lack of data available for CWs can limit the effectiveness of the AI models (Savvidou et al., 2024; Bao et al., 2023).

Conventional water quality indicators such as COD, BOD_5, nitrogenous substances, and phosphorus substances are the most commonly focused indicators in current AI-based water quality monitoring research (Table 2). This focus is partly because these indicators are challenging to measure or have latency issues. For instance, BOD_5, a common indicator for reclaimed water, requires monitoring dissolved oxygen changes over five days, posing significant obstacles for daily monitoring. Moreover, these indicators are more user-friendly for researchers in terms of raw data collection difficulty compared to CECs, which might also contribute to the higher research interest. In terms of importance, these fundamental water quality indicators were the primary evaluation criteria when WWTPs were initially established, but they lack sophistication in the latest reclaimed water reuse standards. While conventional indicators (e.g., BOD_5, etc.) dominate AI-based monitoring studies, their relevance to reclaimed water reuse is limited. Current AI models rarely include CECs, partly due to the difficulty in obtaining high-resolution data. However, AI is increasingly applied in analytical chemistry to support CECs detection. Models such as ANN and SVM are used to predict chromatographic retention times and optimize HRMS-based identification of PPCPs. These tools significantly reduce detection time and increase reliability in complex samples, offering a potential bridge to real-time CECs management. Despite significant analytical research has explored the detection of CECs in laboratory and tertiary treatment settings (e.g., membrane technology), AI applications remain limited in the context of real-time process monitoring and operational control. Most current approaches focus on offline detection rather than on dynamic, in-process sensing or predictive modelling of CECs for reuse scenarios. (Nam et al., 2023; Jaffari et al., 2023; Fu et al., 2023). Although current AI models can indirectly optimize CECs monitoring by enhancing instrument performance (Li et al., 2024b), AI technology still lacks the capability to compute CECs concentrations through data-driven methods (such as soft sensing). This ability is crucial for future water quality assurance of reclaimed water and cost reduction in monitoring. Thus, in the future development of water quality monitoring, AI technology will likely need to more efficiently integrate AI models with Internet of Things (IoT) technology to enhance the automation, responsiveness, and processing capabilities of wastewater treatment systems for reuse. These technologies will enable real-time monitoring of a broader range of water quality parameters, such as ARGs. This will not only provide more comprehensive water quality information but also trigger immediate warnings at the first signs of contamination, greatly improving treatment efficiency and the safety of reclaimed water reuse.

While the reviewed studies offer promising results in terms of model accuracy and performance metrics (e.g., $R = 0.87$ for COD prediction), a deeper analysis reveals significant limitations. Many models rely on small, site-specific datasets that lack diversity, reducing the generalizability of the results to other WWTPs. For instance, some models trained under controlled lab-scale conditions may perform poorly in full-scale operations due to unaccounted environmental variability. Additionally, overfitting remains a concern, particularly with complex architectures such as DNNs and LSTMs, which may capture noise instead of meaningful patterns when trained on limited or unbalanced datasets. The absence of cross-validation and external dataset testing in many studies further hinders confidence in the reported performance. Future reviews and experimental designs should systematically include dataset characterization, overfitting controls, and performance benchmarks across multiple WWTP scenarios to provide more robust conclusions.

4.2. Intelligent control

Control technology for wastewater treatment is crucial for optimizing processes and ensuring effluent quality. However, wastewater treatment is a complex nonlinear system filled with numerous slow and uncertain biological and chemical mechanisms. This complexity makes traditional control methods and strategies ineffective in responding to the real-time demands of water treatment processes, preventing low-energy and low-cost operations (Sun et al., 2017; Ao et al., 2023). In recent years, AI-based intelligent control technology has gained widespread attention for its outstanding performance in nonlinear control within wastewater treatment. AI applications in this domain include parameter adjustment, macro control strategies, and frameworks (Xu et al., 2022).

DO is the most focused parameter. Aeration, which provides DO, is the most energy-consuming part of the entire wastewater treatment process, accounting for up to 50 % of the energy consumption (Qambar and Al Khalidy, 2022; Wang et al., 2024b). Therefore, controlling DO is crucial for energy savings and cost reduction in WWTPs. AI's involvement in DO control mainly encompasses finding the DO setpoint (aeration demand) and optimizing the control system. In terms of DO setpoint identification, AI models can effectively predict and dynamically adjust the optimal DO setpoint using common parameters from the wastewater treatment process (such as temperature, flow rate, DO content, and water quality indicators), avoiding the fixed blower setting at 2 mg/L (Qambar and Al Khalidy, 2022; Wang et al., 2023b; Lu et al., 2021). For example, researchers have used influent flow, BOD_5, and MLSS as inputs to an RF AI model to successfully predict the optimal DO concentration, helping the WWTP reduce operational energy consumption (Qambar and Al Khalidy, 2022). Another example from a large WWTP in China, showed that multiple classical AI models could predict the optimal aeration demand, reducing energy consumption by 16 % (Wang et al., 2023b). Notably, besides classical AI models, reinforcement learning models have also shown promising performance in DO setpoint identification (Croll et al., 2023; Du et al., 2023). Reinforcement learning can help agents adjust actions (DO concentration setpoints) based on environmental states (e.g., current DO concentration) and reward signals (e.g., reduced aeration energy consumption), achieving optimal DO setpoints and energy reduction. Unlike DO setpoint identification, control system optimization focuses on adjusting internal parameters of the operating system to better track the DO setpoint (Han et al., 2019a; Man et al., 2018). For instance, the commonly used PID controller in WWTPs can effectively adjust PID parameters (kp, ki, kd) when combined with AI techniques like FL and ANN, improving DO setpoint tracking and preventing the actual DO concentration from deviating far from the setpoint (Man et al., 2018; Li et al., 2022). Besides PID control systems, AI can also optimize MPC, ABAC, and other control or operating systems for similar purposes (Han et al., 2019a; Wang et al., 2023c; Newhart et al., 2020).

Apart from parameter adjustment, AI can enable intelligent control of WWTP processes by establishing macro control strategies and frameworks (Heo et al., 2021; Wang et al., 2021). For example, researchers have proposed a control framework based on AI models (comprising RF models, DNN models, variable importance measure analysis, and partial dependence analysis). This framework effectively links effluent quality with operational processes, helping WWTPs better identify variables with optimization potential in various processes (Wang et al., 2021). It's important to note that regardless of the AI control method used, ensuring water quality is the prerequisite for optimizing energy consumption. Some optimization methods may overly focus on a single target, leading to non-compliance with other standards. AI techniques can find a balance between energy consumption and effluent quality, which is crucial. Multi-objective optimization techniques like PSO and MOALO can typically optimize multiple conflicting objectives, finding the best balance between energy consumption and water quality (Niu et al., 2022b; Zhou et al., 2023). In wastewater treatment for reuse, it is essential to minimize operational costs and energy consumption while maximizing pollutant removal efficiency and protecting the environment of receiving water bodies. Using multi-objective optimization models allows for finding the best balance between these goals. AI systems can learn from historical data to predict costs, energy use, and treatment efficiency under different operational settings. Then, with the help of multi-objective optimization models, AI can automatically adjust the treatment process to accommodate changing input loads and environmental conditions.

From the above control methods, it's clear that AI-based control technology can effectively help WWTPs reduce energy consumption, lower costs, and ensure water quality. However, existing intelligent control technologies are often established to meet wastewater discharge standards rather than reclaimed water standards. For instance, water quality standard parameters (EQI), commonly used in control technology development, typically consider organic matter, suspended solids, and nitrogen content in the effluent (Han et al., 2019a). Some reinforcement learning-based control technologies even set the reward mechanism entirely based on nitrogen content (Croll et al., 2023; Zhou et al., 2023). As previously mentioned, the latest European reclaimed water standard (Regulation (EU) 2020/741) has removed nitrogen content limits. This indicates that current AI control technologies may not be conducive to future reclaimed water reuse processes. Therefore, existing DO intelligent control needs to be independently developed for reclaimed water reuse to promote wastewater recycling. This shift could significantly impact WWTP DO control, as current methods, although reducing energy consumption, still can't achieve substantial reductions under current effluent quality constraints (typically only achieving about 10 % optimization while maintaining existing EQI levels) (Croll et al., 2023; Zhou et al., 2023). If nitrogen content constraints are removed, existing control strategies can further reduce aeration energy consumption by decreasing the DO required for ammonia nitrification, further lowering costs for reclaimed water reuse. Moreover, a significant gap in current intelligent control strategies is the lack of consideration for CECs, which require particular attention in reclaimed water reuse, especially in agricultural applications. Developing AI control models and systems that integrate CECs monitoring and response mechanisms is a key direction for future reclaimed water treatment control technology. For example, using ML models to predict the behaviour and removal efficiency of CECs, and integrating these predictions into real-time control strategies, can optimize treatment processes and ensure water safety and quality for agricultural needs. Current AI-based control systems have been primarily optimized for meeting conventional discharge standards. However, reclaimed water for irrigation must meet specific safety standards (e.g., Regulation (EU) 2020/741). Therefore, future AI models should align with reclaimed water quality requirements by reprioritizing control objectives based on e.g., microbial risks, salinity, the presence of CECs, etc. This adaptation will make AI applications more relevant to agricultural reuse systems. To close the loop between detection and action, future AI-based control systems must incorporate CECs-specific indicators, either directly via online detection, or indirectly through predictive models that infer CECs behavior from surrogate parameters. Integrating analytical detection advances into control strategies will be crucial to ensure treatment systems meet emerging water reuse quality standards.

4.3. Fault diagnosis

Fault diagnosis is crucial for ensuring the normal operation of WWTPs. Conventional detection methods are often ineffective for complex, high-dimensional, and nonlinear systems and datasets (Newhart et al., 2019; Abid et al., 2020). Given that modern WWTPs have numerous sensors generating vast amounts of data, AI models can convert fault diagnosis into classification or regression problems. Classification problems can identify whether new data belong to normal or abnormal categories, thereby recognizing faults (Mamandipoor et al., 2020). Regression problems are primarily used for predicting fault evolution (Liu et al., 2023b). AI models such as SVM, ANN, and PCA are widely employed in fault diagnosis (Liu et al., 2023b; Wang et al., 2020; Kazemi et al., 2021).

Regarding specific fault types, sludge bulking and sensor faults are commonly addressed by AI models. Sludge bulking is considered one of the most severe issues in over 50 % of WWTPs, primarily due to the excessive growth of filamentous bacteria, which makes separating activated sludge difficult, degrading effluent quality, and increasing operational costs (Liu et al., 2016). One way to diagnose sludge bulking is by using AI models to predict key parameters of sludge bulking, such as sludge volume index (Han et al., 2019b; Liu et al., 2023c; Chang et al., 2024). For instance, researchers used online sensor data (DO, pH, temperature) as inputs to a fuzzy neural network to predict the sludge volume index, achieving sludge bulking monitoring (Han et al., 2019b). Additionally, AI models combined with computer vision can also monitor sludge bulking (Zhao et al., 2019a; Inbar et al., 2023). For example, studies have reported that CNN models can effectively identify microorganisms, filaments, and flocs in activated sludge from microscopic images, which is significant for monitoring sludge bulking (Inbar et al., 2023). Sensor faults, often caused by harsh environments such as humidity and corrosion, pose challenges to the safe and reliable operation of WWTPs. AI techniques can also monitor sensor faults. For instance, AI techniques like SVM and PCA have been reported to detect various typical DO sensor faults (Ghinea et al., 2023; Luca et al., 2021).

Thus, AI can effectively support wastewater treatment technologies by diagnosing faults, ensuring the smooth operation of the treatment process and the safety of reclaimed water. For example, AI models can monitor pumps and valves in real-time, identifying performance degradation and predicting potential equipment failures that could disrupt treatment. This is especially important in reclaimed water production, which often requires more steps and expensive equipment than regular wastewater treatment to ensure safety and quality. By using AI, maintenance costs are reduced, reliability is increased, and sustainability is supported. Although AI shows great potential for fault detection, there is still a lack of real-world application cases in reclaimed water treatment. Furthermore, balancing inference speed and accuracy remains a key research area for ensuring timely and precise fault detection. This is critical for maintaining water quality and the integrity of the system.

4.4. Special applications in tertiary treatment technology

Tertiary treatment technologies are strictly required by standards and are indispensable for wastewater treatment and reuse processes. Among these, membrane technology and disinfection are explicitly recommended by the latest European standard. NBS, as one of the most highly regarded green processes under current research, is also frequently applied in tertiary treatment (Mancuso et al., 2021). Therefore, this section will explore the special applications and advancements of these three key approaches in wastewater treatment.

Membrane technology is widely used in wastewater treatment for reuse due to its efficient separation capabilities. However, membrane fouling remains a major barrier to its broader application. The introduction of AI offers new opportunities to address this challenge. Compared to traditional mechanical/mathematical models, AI models can better capture the complex relationships in the membrane fouling process, thereby improving prediction accuracy and sensitivity (Niu et al., 2022a; Kamali et al., 2021; Cairone et al., 2024). Common AI tools for membrane fouling prediction include ANN, FL, GA, and PSO (Mittal et al., 2021; Shirazian and Alibabaei, 2016). Parameters such as transmembrane pressure, membrane type, water temperature, pH, and conductivity are used as model inputs to predict the extent of membrane fouling (typically represented by permeate flux and transmembrane pressure) (Jawad et al., 2020; Hu et al., 2021; Nourbakhsh et al., 2014). It is worth noting that the most critical model inputs may differ depending on the membrane technology. For example, studies indicate that while solute concentration is a vital input variable for RO, AI models for NF tend to prefer pH and filtration time (Niu et al., 2022a). Recent studies have utilized various AI models (such as ANN, RF, and LSTM) to accurately predict transmembrane pressure variations across different operational cycles of membrane technology, using nearly four years of high-resolution data from real wastewater treatment plants. This demonstrates that AI can play a significant role in the practical application of membrane technology (Kovacs et al., 2022).

In addition to predicting membrane fouling, AI models can help identify fouling mechanisms. AI models can further determine the contributing factors to membrane fouling. For example, researchers have used AI models to identify conductivity and pH as key factors affecting membrane fouling in membrane bioreactors (Viet and Jang, 2021). AI models with image processing capabilities, such as CNN, can also predict and identify features of fouling layers from fouling images (Im et al., 2021; Shim et al., 2021). Exploring interfacial relationships is crucial for understanding pollutant adhesion processes and fouling mechanisms. AI technology can effectively predict interfacial interactions on membrane surfaces, providing insights into fouling mechanisms (Zhao et al., 2019b). Thus, using AI technology, researchers can more accurately identify and quantify the relative contributions of these fouling mechanisms, allowing for the development of more effective cleaning and maintenance strategies for membrane modules in reclaimed water production (Niu et al., 2022a). This not only helps extend membrane lifespan but also significantly reduces operational costs. In the future, combining AI with online monitoring will enable real-time membrane fouling control and dynamic adjustments, ensuring stable and safe water quality. With ongoing advancements in AI, further integration with IoT can optimize membrane system management, meeting increasing demands for water quality and efficiency in wastewater treatment. Therefore, AI can effectively participate in membrane fouling prediction and control processes, significantly contributing to membrane fouling control, reducing operating costs, and promoting the widespread application of membrane technology in reclaimed water. A complementary frontier is the use of AI models for data-rich analysis of advanced analytical techniques such as HRMS, LC-MS/MS, and NMR. These methods generate complex datasets which can be interpreted using ML models to enhance the identification and quantification of trace-level CECs. AI-enhanced interpretation enables early detection of compounds such as PFAS, pharmaceuticals, and other CECs. Despite this progress, these systems are not yet linked with real-time WWTP control loops, highlighting a gap between advanced detection and operational decision-making.

Disinfection is a necessary process in reclaimed water reuse, as it effectively inactivates pathogens present in wastewater. Traditional disinfection models cannot respond promptly to nonlinear factors during disinfection due to fluctuating water quality conditions (Mao et al., 2022). AI technology can better capture these complexities, demonstrating excellent performance in disinfection. Classical AI models like ANN and GA are also widely used in disinfection processes (Ding et al., 2024; Liu et al., 2023d; Hong et al., 2020). AI techniques can optimize various traditional and advanced disinfection processes, including disinfectant dosage optimization, energy consumption optimization in high-energy processes like ozonation, and pathogen inactivation prediction (Ding et al., 2024; Khawaga et al., 2019; Foschi et al., 2021). In traditional disinfection processes, AI models such as ANN can effectively predict chlorination behavior in secondary wastewater. By integrating ANN models with control systems, the chlorination process can be optimized to maximize efficiency, reduce chlorine disinfectant dosage and costs without exceeding plant budgets (Khawaga et al., 2019). AI models can not only optimize the chlorination process on their own but can also be combined with traditional water system models to further improve specific disinfection parameters such as initial chlorine dosage and dosing points (Mao et al., 2022). In the application of ozone disinfection, AI technologies can also effectively optimize the process. For instance, various types of AI models have been shown to predict bacterial inactivation levels during ozone disinfection (Kadoya et al., 2021). In UV disinfection, AI technologies differ from the hydraulic models used in traditional UV research. AI models do not require the extensive parameter calculations involved in hydraulic models, which reduces the difficulty of research and practical application. Models such as ANN can effectively contribute to pathogen prediction and UV reactor design, enhancing efficiency and saving energy (Xu et al., 2014). However, it is worth noting that most research involving AI technologies for pathogen prediction in water reuse processes focuses on bacteria. In reality, viruses are also significant pathogens impacting the safety of reclaimed water. They can affect human health through routes such as agricultural product residues and aerosols, potentially harming the gastrointestinal and respiratory systems (Wang et al., 2024c). Additionally, for novel disinfection processes such as PAA disinfection and photocatalysis, AI models can similarly achieve effects comparable to traditional disinfection methods (Teo et al., 2022; Wei et al., 2020). These models have been applied to predict the inactivation of key microbial species such as *Escherichia coli*, *Enterococcus faecalis*, Norovirus, and Rotavirus under chlorination, UV, and PAA-based disinfection. ANN and GA models have shown high accuracy in estimating pathogen log removal rates as a function of dose, pH, contact time, and turbidity (Ding et al., 2024). Mechanistically, these models often incorporate surrogate parameters (e.g., UV254 absorbance) that correlate with virus capsid integrity or bacterial membrane disruption. Despite these advancements, virus-focused AI modelling remains limited and requires further research to capture aerosol transmission risks in open-field reuse applications.

Moreover, AI technology can help effectively identify and control disinfection by-products, including regulated by-products (such as THMs) and unregulated ones (such as HANs), to reduce secondary pollution issues following wastewater disinfection (Lin et al., 2024; Li et al., 2021). For instance, researchers used AI models like ANN, and RF, with inputs such as disinfectant dosage, reaction time, and pH, to accurately predict disinfection regulated by-product (THMs) concentrations and identify key influencing factors using interpretable AI tools (Sikder et al., 2023). Unregulated disinfection by-products, such as HANs, can also be identified and analyzed using AI models (Lin et al., 2018). Therefore, AI technology can effectively optimize disinfection processes, significantly enhancing disinfection efficiency, ensuring reclaimed water safety, and reducing disinfection costs.

In most cases, NBS are applied during tertiary treatment, either as a final polishing step after secondary treatment or to address specific polluted streams, such as reducing the nutrient load from agricultural runoff (Mancuso et al., 2021). Since NBS involve using natural processes to treat wastewater with minimal use of technology, AI can be applied only to a small component of these systems. AI and ML are applied to NBS, such as CWs, to enhance their efficiency, predict outcomes, and optimize performance. AI can help identifying the optimal design and operational conditions for NBS, such as flow rates, retention times, and nutrient removal efficiency. In the study of Singh et al. (2023), ML approach was applied on two vertical flow CW having different media i.e., expanded clay and biochar, to understand critical parameters and effluent quality. The authors tested different algorithms (RF, generalized linear model, and SVM) for monitoring effluent parameters such as BOD, COD, nutrients, solids, and metallic substances. In another study, two vertical flow CWs using expanded clay (VF CW1) and biochar (VF CW2) were monitored for organic matter (BOD_5) and nitrogen (NH_4-N) removal. The study leveraged ML models to predict effluents, with RF, generalized linear models (GLM), and support vector machines (SVM). The ML models demonstrated high accuracy, achieving coefficients of determination (R^2) of up to 90.1 % for BOD_5 in VF CW2 (Nguyen et al., 2021).

4.5. Released patents for AI in wastewater treatment and agricultural reuse systems

Several AI-based systems for wastewater reuse have been patented in recent years. For instance, US Patent No. 10,976,354 describes an AI-driven optimization platform for membrane bioreactor operation, including predictive control based on influent variability. Similarly, CN112899841A discloses a multi-sensor AI irrigation controller that integrates water quality inputs with weather forecasts. These patents highlight the growing intersection of AI and practical reuse applications, supporting the transition from lab-scale studies to deployable technologies.

4.6. Data challenges in AI-driven wastewater reuse

Data quality is one of the most limiting factors in AI model development for wastewater and irrigation systems. In harsh environments like WWTPs, sensors frequently degrade due to fouling, corrosion, or humidity, leading to noisy or missing data. Moreover, there is a lack of standardized formats and preprocessing protocols, making multi-source data integration problematic. For example, discrepancies in units, sampling intervals, and calibration techniques hinder the development of transferable models. Another concern is the scarcity of high-resolution datasets for CECs, ARGs, and microbial indicators relevant to reuse scenarios. To address these challenges, future work should emphasize the adoption of robust preprocessing techniques (e.g., interpolation, outlier filtering, and normalization), and promote the creation of shared open-access repositories with annotated datasets for reclaimed water quality. Data augmentation and synthetic data generation via generative AI may also offer interim solutions where real-world data is insufficient.

5. Role of AI in agricultural irrigation

While AI applications have advanced agricultural irrigation through precision tools and improved water use efficiency, a critical challenge remains largely unaddressed: the inconsistency between the water quality outputs from AI-assisted wastewater treatment (as highlighted in Section 4) and the actual requirements for safe and effective agricultural reuse. Current AI models used in wastewater treatment are primarily calibrated to meet effluent discharge standards and fail to detect emerging contaminants such as CECs (e.g., pharmaceuticals, antibiotics, ARGs), which are essential for ensuring reclaimed water safety in agriculture. This misalignment introduces tangible risks for AI-driven irrigation systems that rely on real-time or predicted water quality inputs. Consequently, the efficacy of these AI tools in agriculture is contingent upon a more robust integration with upstream water treatment data, particularly concerning water quality risks that may directly impact soil health, crop safety, and food security. However, the integration of AI into agricultural irrigation systems has significantly enhanced water management efficiency, productivity, and sustainability. By combining AI with DNN and the IoT, irrigation systems can now operate with a high degree of precision, utilizing real-time data to make informed decisions on water usage. AI-driven solutions have been shown to optimize irrigation practices, leading to measurable efficiency improvements. For instance, the implementation of AI systems has been associated with productivity increases of up to 40 % in some cases (Anil Chougule and Mashalkar, 2022). Predictive models such as NITRINET, developed to optimize fertigation in pressurized irrigation systems using reclaimed water, predict water quality indicators crucial for plant growth. This optimization helps improve water use efficiency, reduces fertilizer consumption, and mitigates environmental impacts, particularly in semi-arid regions (Gómez-Lucena et al., 2024). The reuse of reclaimed water in irrigation offers a dual benefit of addressing water scarcity issues while also reducing the environmental footprint of agricultural practices. AI-based systems in conjunction with reclaimed water management allow for more effective use of water resources, ensuring that the water quality remains within suitable parameters for crop growth and reducing dependency on freshwater sources. However, the safety of using such reclaimed water in AI-based irrigation systems cannot be guaranteed if some water quality indicators, such as the presence of CECs, residual salinity, etc., are not adequately monitored or communicated from upstream treatment plants. For instance, if antibiotics or pharmaceutical residues persist undetected in the effluent due to limitations in AI-based monitoring at WWTPs, these substances may accumulate in soil or crops, undermining AI-based yield prediction models or triggering long-term soil health degradation. Such omissions can lead to biased or misleading outputs from AI-based forecasting systems, which often assume consistent and clean irrigation inputs. Moreover, AI models trained for precision irrigation (e.g., fertigation optimization, evapotranspiration scheduling) typically rely on historical or sensor-derived environmental data, but they rarely incorporate dynamic feedback loops that account for reclaimed water quality variability. This lack of integration means that current AI-driven irrigation platforms are effectively quality-blind, indicating they optimize delivery without fully assessing input safety.

AI-enhanced simulation tools, including AquaCrop, WinSRFR, and SALTMED, have been widely validated across different agricultural settings, to predict water distribution, crop yields, and soil moisture under various environmental conditions (Ramadan et al., 2023). These tools enable farmers to adapt their irrigation practices to changing climates and soil conditions, ensuring efficient water use and maximizing crop output. In addition to simulation tools, AI-driven sensor networks, such as wireless sensor nodes, provide real-time monitoring of reclaimed water quality, ensuring that irrigation water is safe and suitable for crop use (Aldegheishem et al., 2023). These sensors, being low-cost and durable, measure critical parameters such as pH and temperature, contributing to the overall management of irrigation systems, particularly in agricultural settings. Moreover, the integration of AI with IoT sensors allows for the real-time tracking of reclaimed water quality, enabling dynamic adjustments in irrigation practices to maintain optimal conditions for crop health while ensuring sustainable water usage.

The application of IoT-based weather monitoring systems further enhances irrigation practices by considering variables such as humidity, air temperature, wind speed, solar radiation, and soil moisture control. These systems allow for a more accurate evaluation of crop environments, helping optimize irrigation strategies (Ganesh, 2023). When integrated with AI, IoT-based weather and sensor networks enable the development of precision irrigation systems that dynamically adjust water delivery based on real-time environmental data, thereby reducing water wastage and ensuring crops receive the required amount of moisture. This concept is exemplified in the SWAMP project, as described by Kamienski et al. (2019), which developed an IoT-based smart water management platform for precision irrigation, deploying pilots in Brazil, Italy, and Spain. The SWAMP platform's flexibility and adaptability across diverse settings are aligned with the need for customized solutions in agriculture, particularly in managing irrigation and water distribution. Kamienski et al. (2019) also highlight the role of reclaimed water in their platform, demonstrating how real-time data from IoT-enabled systems can be used to manage the irrigation process efficiently, using non-traditional water sources while maintaining crop productivity and sustainability.

Furthermore, AI can enable predictive analysis based on historical data, allowing for more accurate forecasting of irrigation needs and crop yields (Monchusi et al., 2024). ML algorithms, such as RF and support vector regression, are used to develop low-cost, real-time forecasting tools that assist in managing irrigation strategies, especially in developing regions (Wei et al., 2024). These algorithms analyze data from IoT-enabled sensors, including weather conditions, soil moisture, and crop growth rates, to predict optimal irrigation times, thus improving crop yields while minimizing resource waste. The approach of Monteleone et al. (2020) for modeling agricultural operations management also emphasizes the importance of these predictive models, particularly in irrigation planning and scheduling, which are key factors in improving irrigation efficiency and productivity. By incorporating reclaimed water into these predictive models, AI systems can further optimize water usage, especially in regions where freshwater resources are limited. This allows for better resource allocation and the development of strategies that balance water availability with agricultural needs.

A major risk arises when models use real-time reclaimed water without incorporating metadata on effluent composition. For example, excess salinity in reclaimed water, if undetected, can lead to progressive soil salinization, which not only diminishes soil fertility but also biases models that predict crop growth based on soil electrical conductivity. Similarly, bioaccumulation of CECs in leafy vegetables or fruiting bodies is a recognized risk when irrigation systems apply inadequately treated water, with implications for food safety that AI models currently do not flag or mitigate.

DL techniques, including convolutional and recurrent neural networks, also play a crucial role in smart irrigation systems by processing high-dimensional data, such as satellite imagery and sensor data. These techniques enable advanced tasks such as crop health monitoring, disease detection, and yield prediction (Wei et al., 2024). In intelligent irrigation systems, AI algorithms such as FL and DL help handle environmental uncertainties, allowing systems to make real-time adjustments in irrigation levels to optimize water use (Neji and Mechri, 2024).

Finally, AI-based surveillance systems support crop monitoring, pest detection, and soil health diagnostics, providing insights that help farmers plan irrigation schedules and planting strategies for maximum yield (Javaid et al., 2023). Monteleone et al. (2020) similarly underscore the importance of surveillance and real-time data in precision agriculture, particularly in irrigation management, as part of a broader framework for Agriculture 4.0. Kamienski et al. (2019) also conducted a performance analysis of the SWAMP IoT-based platform, evaluating its scalability and efficiency in different pilot scenarios. The study revealed critical insights into how the platform can be optimized for large-scale deployment, ensuring robust and sustainable irrigation practices across a wide range of agricultural contexts. These findings are particularly relevant for the incorporation of reclaimed water into irrigation systems, where real-time monitoring and predictive analytics ensure water quality remains consistent, reducing the risks associated with using non-traditional water sources in agriculture. As irrigation systems evolve, AI technologies continue to transform water management in agriculture, making it more efficient, sustainable, and adaptable to changing environmental conditions. Through enhanced water use efficiency, accurate forecasting, and dynamic decision-making, AI is addressing critical challenges such as water scarcity and climate change in agriculture (Gao et al., 2023b).

5.1. Bridging the gap: AI requirements for integrating wastewater treatment and agricultural systems

To fully realize the potential of AI in reclaimed water reuse, future systems must be designed with an integrated architecture that links wastewater treatment outputs to downstream agricultural decision-making. This means that AI-based irrigation platforms must become water-quality aware, capable of adjusting irrigation frequency, dosage, or exclusion zones in response to real-time or predicted contaminant levels from WWTPs. To support this concept, Fig. 4 illustrates a conceptual diagram linking wastewater treatment processes, tertiary treatment, AI-based monitoring, and agricultural irrigation.

One promising approach is the development of coupled AI systems, where models used in WWTPs to estimate CECs concentrations or membrane fouling risks are linked through APIs or data-sharing protocols to agricultural AI platforms. For instance, if an AI model in the WWTP predicts a spike in certain antibiotics or ARGs, the irrigation model could automatically delay watering for sensitive crops, or redirect flows to crops with lower bioaccumulation risks. To concretely illustrate integration potential, consider a real pilot-scale application in Northern Italy reported by Foglia et al., where an AnMBR treating municipal wastewater under high-salinity coastal conditions delivered effluent meeting EU reuse standards; when integrated with downstream precision irrigation, it enabled reuse in fertigation systems compliant with crop-specific salinity thresholds. In a case study near Milan, combining AnMBR effluent with irrigation networks led to reduced soil salinity accumulation over the season (roughly 22 %) and improved crop safety, as documented through LCA and LCC analyses indicating both environmental and economic advantages (Foglia et al., 2020, 2021). Moreover, AI-based agricultural tools should incorporate dynamic feedback loops: learning from crop health data, soil test results, and food residue analyses to re-calibrate risk assessments and irrigation strategies over time. This would allow the creation of adaptive AI systems, where predictions are not only based on historical patterns or climate, but also on water treatment quality metrics. Finally, the incorporation of explainable AI (XAI) and uncertainty quantification is critical. When water quality predictions carry uncertainty, especially regarding CECs, irrigation models must communicate this to users, and provide fallback strategies to minimize ecological or food safety risks. These hybrid systems could substantially close the loop between wastewater treatment and precision agriculture, fulfilling the circular economy promise of safe, data-informed water reuse. Recent literature underscores the need for this integration. For example, Radini et al. (2023) and Verlicchi et al. (2023) have emphasized the role of digital risk management and prioritization frameworks for safe reuse of wastewater in agriculture, particularly under European regulations. Building on these insights, AI must evolve beyond isolated applications and towards end-to-end, interoperable architectures that account for water quality, health impacts, and adaptive system behavior.

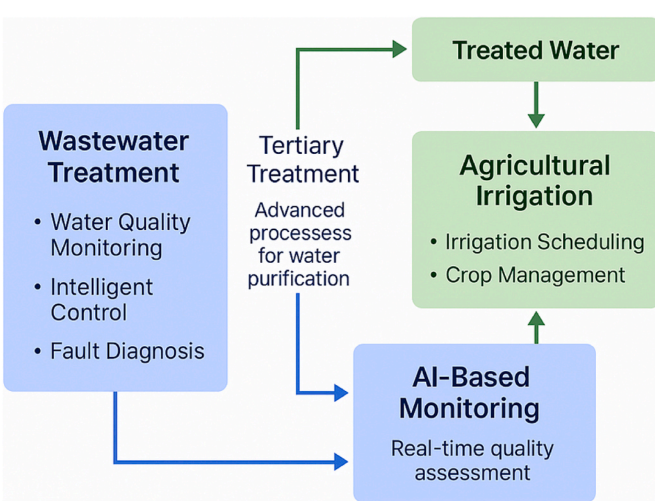

Fig. 4. Conceptual diagram connecting wastewater treatment and agricultural irrigation.

6. Perspectives and suggestions

From the review above, it is clear that AI technology demonstrates significant potential in wastewater treatment and water reuse agricultural systems. However, when re-examined in the context of reclaimed water needs, there are still limitations and underexplored areas in existing AI applications that require further research and improvement. Below are the current research gaps and future recommendations:

(i) Enhancing AI's capability in detecting CECs: while most existing AI models focus on conventional pollutants (e.g., COD, BOD_5), significant progress has been made in using AI to support CECs detection in analytical laboratories, particularly through tools such as HRMS combined with ML models for RT and CCS prediction. However, these models are rarely applied to real-time control contexts. Future research should bridge this divide, ensuring that AI detection tools are operationalized within the treatment plant to guide dynamic interventions and optimize removal;

(ii) Developing AI models based on reclaimed water standards: most AI research in WWTPs is built around wastewater discharge standards, often neglecting the specific water quality needs of reclaimed water. Future studies should focus on developing models tailored to reclaimed water standards to further reduce energy consumption and improve water quality;

(iii) AI in decision support systems: development of AI-powered decision support systems that dynamically integrate reclaimed water quality data from WWTPs with agricultural irrigation scheduling. Such systems should enable real-time, quality-aware water allocation based on predicted crop sensitivity, soil conditions, and contaminant presence, closing the feedback loop between treatment output and field-level demand;

(iv) Applying hybrid and more advanced AI models: hybrid AI models often outperform single models in predictive accuracy. Therefore, developing and applying hybrid models should be a priority. Additionally, advanced AI models such as large language models could improve prediction but need optimization to balance inference speed and accuracy in real-time scenarios;

(v) Improving data pre-processing methods: given the harsh environments of WWTPs, sensor failures often lead to data gaps or anomalies. Efficient data preprocessing methods are critical for maintaining high predictive accuracy in AI models, even with low-quality data;

(vi) Increasing the use of explainable AI tools: AI models are often seen as "black boxes", making their decision processes hard to understand. Explainable AI (XAI) tools such as SHAP and LIME can offer insight into model decisions, particularly in "black box" architectures such as deep neural networks. Integrating such tools can enhance trust among WWTP operators and regulators, enabling model auditing and compliance verification for reclaimed water reuse;

(vii) Expanding research on the transfer application of AI technology between different WWTPs: due to the regional and process heterogeneity of WWTPs, current AI models are often developed for individual WWTP. Transferring trained models to other WWTPs with similar processes or modes can effectively reduce model development and training costs, promoting the further application of AI technology in WWTPs;

(viii) Expanding AI applications in full-scale water treatment facilities: while AI research in water quality monitoring is extensive, its real-world application in full-scale WWTPs is limited. Large-scale plants face more complex challenges and interference factors, so further testing in large-scale scenarios is necessary to assess AI performance in real-world environments and identify paths for optimization;

(ix) Bridging lab-based detection and plant-based control: a clear research gap persists between AI-driven analytical detection of CECs in laboratory environments and the implementation of AI-based control strategies for dynamic CECs removal in WWTPs. Establishing this connection, via soft sensing, surrogate indicators, or hybrid analytical-operational models, should be a research priority to ensure reclaimed water safety in real-time applications. Moreover, while previous research identifies the need for better CEC detection, it does not specify which AI methods may be most effective. CNNs, in combination with HRMS, have shown high promise for identifying CECs through retention time and mass fragmentation pattern predictions. Additionally, RL can be employed to dynamically adjust operational parameters such as chemical dosing or membrane cleaning cycles based on predicted CEC concentrations. These targeted approaches should be explored in future research agendas to improve model specificity and application relevance;

(x) Enhancing data quality and availability: AI algorithms, especially data driven approaches, such as machine learning and deep learning, require large volumes of data for model training. An increase in data volume can enhance the accuracy of crop yield and water usage predictions.

(xi) Considering cost-effectiveness and policy frameworks: beyond technical performance, the success of AI-driven reuse systems depends on cost-effectiveness and policy support. Initial implementation of AI in WWTPs entails high computational and training costs, yet potential long-term savings include up to 10–15 % reduction in energy usage, 20 % extension of asset lifespan, and lower manual labor requirements. Policy instruments such as the Regulation (EU) 2020/741 and incentives for digital transition can accelerate adoption. Moreover, integrating AI into regulatory frameworks would require standards for model validation, interpretability, and auditability. Future work should incorporate cost-benefit analyses and socio-economic assessments to guide sustainable deployment.

Despite promising simulation results, real-life deployment of AI in WWTPs and irrigation networks faces key challenges, including sensor reliability, data interoperability, cybersecurity, and model generalizability across sites. Moreover, infrastructure limitations and regulatory inertia can delay integration. Future efforts should focus on AI system validation in full-scale plants, development of standard protocols for model interpretability, and economic feasibility studies under diverse governance conditions. For example, regulatory sandboxes and smart public procurement can facilitate experimentation and scale-up of AI-enabled reuse systems (Radini et al., 2023; Liu et al., 2023b).

Scaling AI solutions from pilot studies to full-scale implementation introduces unique challenges. Computational costs increase significantly with the size and complexity of data streams in large WWTPs and agricultural networks. Furthermore, infrastructure limitations, such as low-bandwidth communication systems or lack of edge computing capacity, can hinder real-time data processing. To overcome these obstacles, modular AI architectures based on cloud-native platforms offer scalability and flexibility. For instance, deploying AI models in federated systems across geographically distributed WWTPs can support real-time learning and adaptation without centralizing sensitive data. Moreover, containerized microservices allow dynamic scaling based on load, enabling efficient resource use across heterogeneous infrastructures. These strategies are crucial for achieving AI deployment at scale.

6.1. Economic and policy implications for AI-driven water reuse

The deployment of AI for wastewater treatment and agricultural reuse must be addressed not only from a technological perspective but also from economic and policy viewpoints. While AI offers substantial operational benefits, such as energy savings, predictive maintenance, and process optimization, these benefits must be evaluated through structured analysis.

Beyond operational benefits, AI adoption must align with economic feasibility and regulatory compliance. While 10–15 % energy savings and up to 30 % equipment lifespan extension present strong incentives, initial deployment costs remain high. Regulatory environments play a decisive role in accelerating or hindering implementation. For instance, the EU Regulation 2020/741 provides a framework for water reuse but does not yet account for AI-based compliance verification. A forward-looking policy approach would include guidelines for AI model validation, auditability, and cybersecurity. Pilot programs under regulatory sandboxes in regions such as California and Spain are already exploring this route. Importantly, economic evaluations should consider not just cost savings but also externalities like reduced chemical usage, improved crop yields, and public health protection. Incorporating AI into subsidy schemes or green transition incentives could further facilitate large-scale adoption.

For example, AI-based aeration control systems can reduce energy consumption by 10–15 % (Alvi et al., 2023), while predictive maintenance algorithms can extend the service life of pumps, membranes, and aeration equipment by up to 30 %, reducing capital replacement costs and unplanned downtime (Liu et al., 2023b). AI-supported monitoring systems also allow for the reduction of chemical inputs and labor costs by replacing manual testing with automated soft sensing (Alvi et al., 2023).

In the agricultural domain, AI-driven irrigation systems have demonstrated the ability to improve water productivity, increase yields, and reduce input costs, especially when using reclaimed water, but these benefits are highly dependent on the quality and reliability of upstream water treatment. If water quality data from WWTPs does not adequately reflect parameters critical for safe reuse (e.g., microbiological quality, CECs), the value proposition of AI in agriculture can be compromised.

To contextualize the economic feasibility of these technologies, Table 3 provides a comparative overview of AI tools and platforms commonly used in wastewater treatment and reuse applications, including typical software environments, licensing models, and associated costs.

Beyond economic feasibility, regulation and public policy are essential drivers for the successful integration of AI technologies in reuse systems. The Regulation (EU) 2020/741 sets minimum requirements for water reuse, especially for agricultural applications, and introduces quality monitoring, risk management, and treatment validation as legal obligations. However, current AI systems are still designed primarily to meet traditional effluent discharge standards (e.g., BOD, TN, TP) and often do not include parameters that might be relevant for reuse, such as CECs, antibiotic resistance genes (ARGs), or microbial targets (Radini et al., 2023). Furthermore, the lack of clear regulatory pathways for AI validation and deployment, coupled with the absence of standardized procedures for model interpretability, data security, and liability, hinders widespread adoption. Policy tools such as AI regulatory sandboxes, targeted public-private partnerships, and innovation funding schemes could help overcome these barriers and promote safe experimentation with AI-based systems under real-world conditions (Verlicchi et al., 2023). Social acceptance also plays a fundamental role in the implementation of AI-driven reuse systems. Reclaimed water use, particularly in food crop irrigation, continues to face skepticism from the public, and AI technologies, often perceived as "black boxes", may exacerbate trust

Table 3
Techno-economic overview of AI tools and software platforms.

Application Area	AI Tool/Framework	Example use case	Software Platform	Estimated Cost (USD)	Notes/Version Info
WWTP Monitoring	ANN	Membrane fouling prediction in MBR systems	MATLAB	~1,200/year (academic)	MATLAB R2023b with Neural Network Toolbox
Irrigation Prediction	RF (Random Forest)	Crop yield forecasting under reclaimed water irrigation	Python (scikit-learn)	Free	Open-source; community support
Fault Detection	LSTM	Predictive aeration control in WWTPs	TensorFlow (Python)	Free	TensorFlow 2.15; GPU-compatible
Hybrid Process Control	FL + GA	Optimizing disinfection dose in tertiary treatment	MATLAB + Simulink	~2,500/year (commercial)	Requires Control System Toolbox
Decision Support Sys.	SHAP + Node-RED dashboards	Real-time dashboard for CEC risk alerts	Python + IoT Middleware	Free (software); hardware-dependent	Integrates explainability into control UI

Note: Cost estimates are indicative as of 2024 and may vary by institution type (academic vs. commercial) and region.

issues if their decisions are not explainable or auditable (Christou et al., 2017). Therefore, AI systems used in water reuse must prioritize transparency and include explainability features (e.g., SHAP, LIME) to communicate recommendations in a user-friendly way to operators, regulators, and end users. In addition, digital traceability and real-time reporting can reinforce confidence in reclaimed water quality and system reliability. To ensure sustainable and socially acceptable adoption of AI in this field, interdisciplinary approaches are required. Future research should focus on techno-economic modelling that integrates AI performance data with full cost accounting, as well as on regulatory studies exploring the governance of AI in environmental and agricultural sectors. Finally, stakeholder engagement and communication strategies are essential to align AI design with user needs, policy requirements, and public expectations, thereby supporting a truly integrated and resilient water reuse infrastructure.

7. Conclusions

This paper provides a comprehensive review of the role of artificial intelligence in wastewater treatment and agricultural water reuse systems. AI models such as ANN, SVM, and RF have been successfully applied in wastewater treatment, encompassing water quality monitoring, intelligent control, fault diagnosis, and specific roles in tertiary treatment. These applications provide effective technical support for improving water quality and reducing costs in key aspects of reclaimed water reuse. AI is also enhancing water management by optimizing agricultural irrigation and improving water efficiency, thus addressing water scarcity and enhancing agricultural productivity. Notably, to better promote reclaimed water reuse and the transition to circular economy, the development of future AI technologies should be based more on reclaimed water quality standards rather than wastewater discharge standards. Additionally, there is still significant room for improvement in AI models, particularly in terms of model accuracy and inference speed. The development of hybrid AI models and the application of advanced AI models may be crucial research directions for addressing these issues. AI is enhancing water management by optimizing agricultural irrigation and improving water efficiency, addressing water scarcity and enhancing agricultural productivity. Special attention should be given to the misalignment between AI control objectives and reclaimed water standards, particularly the overemphasis on removal of specific pollutants (e.g., nitrogen), highlighting the need for regulatory-aware AI design that aligns with future reuse priorities. Moreover, future studies should focus on developing AI models that are more accurate, faster, hybrid, and aligned with evolving regulatory frameworks to support sustainable water reuse.

CRediT authorship contribution statement

Yanbo Liu: Writing – review & editing, Writing – original draft. **Giuseppe Mancuso:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Liliana Petrotto:** Writing – original draft, Investigation. **Stevo Lavrnić:** Writing – review & editing. **Ziyang Dong:** Investigation. **Yu Tian:** Supervision, Formal analysis, Conceptualization. **Jun Zhang:** Writing – review & editing, Funding acquisition, Conceptualization. **Attilio Toscano:** Supervision, Funding acquisition, Formal analysis, Conceptualization.

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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.

Data availability

Data will be made available on request.

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