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Review

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AI-assisted microplastics detection, removal and management: Advances and challenges in wastewater

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Abstract

Microplastics are increasingly recognized as emerging contaminants in wastewater treatment systems. Wastewater treatment plants (WWTPs) receive influent from households, industrial activities, and urban runoff and therefore represent an important pathway for microplastics to enter aquatic environments. In recent years, artificial intelligence (AI) has emerged as a promising tool for improving the detection, monitoring, and management of microplastics in wastewater systems through automated particle identification, data analysis, and predictive modeling. Reported influent concentrations range from approximately 0.4 to 7,216 particles/L, while effluent concentrations typically vary between 0.05 and 994 particles/L, depending on treatment configuration and analytical methodology. Although conventional WWTPs are not specifically designed for microplastics removal, a considerable proportion of particles is retained during treatment. Preliminary and primary treatment stages remove approximately 72% of microplastics, secondary treatment increases removal efficiency to about 88%, and tertiary processes may achieve removal rates close to 94%. However, smaller particles can remain suspended and pass through treatment systems. A large fraction of retained microplastics (60–80%) accumulates in sewage sludge, and when sludge is applied to agricultural soils, concentrations on the order of 10^4 particles/kg have been reported. The accumulation of microplastics in sewage sludge raises further concerns about their fate after sludge disposal or agricultural reuse. Once applied to agricultural land, the retained particles can persist in soils for extended periods and interact with the soil structure, microbial communities, and plant root systems. There is also concern that microplastics in sludge-amended soils may migrate through surface runoff or enter terrestrial food webs over time. Our work suggests that wastewater treatment may not remove microplastics contamination entirely but could rather transfer a fraction of contaminants from aquatic environments to terrestrial systems. The monitoring and removal of microplastics also introduce additional economic and operational challenges for WWTPs, particularly due to the need for advanced analytical techniques and potential upgrades to existing treatment processes. This review summarizes current knowledge on microplastics in WWTPs, focusing on their sources, occurrence, detection methods, and removal technologies, while emphasizing the role of AI-based approaches. Machine learning and computer vision techniques are highlighted for their ability to support automated particle classification, improve monitoring accuracy, and predict treatment performance. By integrating conventional treatment knowledge with data-driven approaches, this review synthesizes research published between 2019 and 2026 and highlights emerging opportunities for improved monitoring and management of microplastic pollution in wastewater systems.

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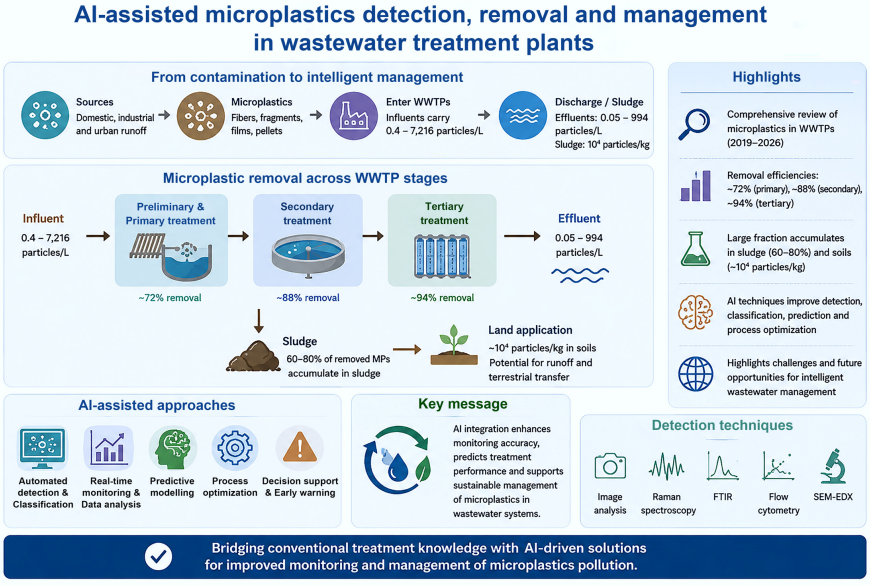
Keywords: Microplastics, Wastewater treatment plants, Artificial intelligence, Machine learning

Highlights

- Integrates microplastics research with recent advances in artificial intelligence.
- AI enhances automated detection and classification of microplastics in wastewater.
- Most retained microplastics accumulate in sewage sludge rather than being eliminated.
- Data-driven models support prediction, monitoring and operational decision-making.
- A conceptual framework is proposed for intelligent wastewater management.

Graphical abstract



Introduction

Emerging contaminants are now regarded as an important issue in aquatic pollution research. This category includes pharmaceuticals, pesticides, personal care products, endocrine-disrupting compounds, antibiotics, dyes, and microplastics[1]. Microplastics are generally defined as plastic particles smaller than 5 mm, although their morphology may differ substantially depending on their origin and environmental degradation processes[2]. Some particles appear relatively regular in shape, whereas others are highly irregular because of fragmentation and weathering processes occurring in natural environments. Due to their persistence, many microplastics do not easily biodegrade and may progressively accumulate in environmental compartments and living organisms. Such accumulation, together with the contaminants associated with these particles, has raised concerns regarding possible environmental and human-health effects. However, the currently available evidence remains limited and in several cases inconclusive. Reported effects include inflammatory responses, respiratory irritation, and possible links with broader health risks that require further investigation[3]. Microplastics have now been identified in a wide range of environmental compartments worldwide. Their presence has been reported in air, water, soils, sediments, and living organisms, demonstrating the extensive environmental distribution of these particles[4, 5]. Several investigations also have confirmed microplastic contamination in both terrestrial and aquatic ecosystems across different geographical regions[6, 7]. In addition, microplastics may enter marine food webs through seafood consumption pathways. This pathway has generated increasing concern regarding potential human exposure to plastic particles and associated contaminants. The transfer of microplastics through seafood chains has been widely discussed in environmental studies[8]. Consequently, increasing research attention is currently directed towards the environmental behavior of microplastics, particularly their sources, transport pathways, environmental distribution, and possible removal strategies[9].

Wastewater treatment plants (WWTPs) represent an important protective barrier for aquatic ecosystems. Their primary function is the removal of organic matter, nutrients, pathogens, and suspended solids before treated effluents are discharged into receiving waters. Most WWTPs, however, are not originally designed for effective microplastics removal. Conventional treatment processes such as filtration, adsorption, and ozonation are commonly applied for contaminant reduction, although their efficiency may decrease considerably when complex mixtures of emerging contaminants are present[10]. Under such conditions, microplastics originating from residential, industrial, and commercial wastewater streams may persist throughout treatment processes and eventually enter natural aquatic environments. More reliable monitoring, detection, and treatment strategies are therefore needed for microplastics in wastewater systems. Traditional water-quality assessment mainly relies on manual sampling procedures, laboratory analysis, and mechanistic modeling approaches. Such methods are generally labor-intensive, time-consuming, and associated with considerable operational costs. Conventional modeling techniques may also fail to adequately represent the nonlinear behavior of complex wastewater treatment systems[11]. The operational management of

modern WWTPs has become even more challenging during recent years. Increasing urbanization, stricter environmental regulations, and progressively more complex influent compositions continue to intensify operational pressures within WWTPs[12]. These conditions have encouraged growing interest in the use of innovative digital and data-driven technologies for wastewater management applications.

Artificial intelligence (AI) refers to a group of computational methods developed to reproduce, at least partly, functions such as learning, reasoning, pattern recognition, and decision making[13]. Machine learning (ML), deep learning, and computer vision are among the most common AI fields, together with natural language processing and other data-driven analytical methods[14]. In contrast to mechanistic models, which usually require prior assumptions about system behavior, AI methods can extract nonlinear relationships directly from data. This is useful in environmental applications, where several variables change simultaneously and their interactions are not always easy to describe with conventional models[15]. AI has already been applied in water-quality prediction and wastewater management. Reported applications include river monitoring, waste forecasting, and water-quality management in different environmental settings[16–18]. Early work on wastewater treatment operation included hybrid AI approaches, with Wen and Vassiliadis (1998) being among the first to apply such methods to treatment facilities[19]. Since then, AI models have been used for the prediction of influent characteristics, effluent quality, energy demand, aeration timing, and sludge-bulking behavior in wastewater systems[20–32]. More recent studies have also introduced soft sensors, optimization methods, and fault-detection tools in WWTP operation[33–42]. These applications mainly aim to improve monitoring, process control, and operational stability in treatment plants.

Despite the extensive literature available on microplastics in aquatic and wastewater environments, most review studies examine occurrence, detection methods, and removal technologies separately. As a result, these research areas are often discussed independently within the existing literature. The incorporation of digital and data-driven technologies into microplastics monitoring and management remains comparatively limited. During recent years, however, AI and related computational approaches have attracted increasing attention in environmental monitoring and wastewater-treatment research. Such methods have been applied in predictive modeling, operational optimization, and process monitoring, while also supporting data analysis and decision-making procedures in treatment systems. In addition, the interactions between particle characteristics, treatment processes, and operational conditions are highly complex and are not always adequately represented through conventional analytical or modeling approaches. At the same time, developments in AI-assisted wastewater monitoring have progressed largely in parallel with microplastics research, with relatively limited integration between these two research fields. To address these limitations, the present review adopts a more integrated perspective linking microplastics research with AI-based monitoring and operational management in WWTPs. Beyond summarizing recent developments, the study also critically examines current limitations associated with monitoring and modeling approaches. Particular emphasis is given to the development of a conceptual framework for AI-assisted microplastics monitoring, integrating data acquisition, predictive modeling, and process-level operational decision support within wastewater treatment systems.

By synthesizing research published between 2019 and 2026, this work aims to move beyond descriptive analysis toward a systems-level understanding of microplastics behavior in wastewater treatment and to identify key directions for the development of intelligent monitoring strategies. This time period was selected because studies specifically focusing on AI-assisted microplastics monitoring and machine-learning applications in wastewater systems became considerably more available during recent years, whereas studies published before 2016 were relatively limited and primarily focused on conventional monitoring and analytical approaches rather than AI-based methodologies. In addition to synthesizing existing literature, this study proposes a conceptual framework for AI-assisted microplastics monitoring in WWTPs. Figure 1 presents the proposed conceptual framework for AI-assisted microplastics monitoring in WWTPs, illustrating the integration of data acquisition, machine-learning-based modeling, and operational decision-support components for predictive wastewater management. The framework is developed based on the integration of findings from recent studies on microplastics occurrence, detection techniques, and AI applications in wastewater systems. The proposed framework consists of three interconnected components: (i) data acquisition, (ii) data-driven modeling, and (iii) operational integration. In the first component, heterogeneous datasets are collected, including conventional operational parameters (e.g., flow rate, turbidity, total suspended solids), laboratory-based microplastics measurements, and imaging or spectroscopic data. These datasets provide the foundation for understanding microplastics behavior under different treatment conditions. In the second component, ML models are applied to identify relationships between microplastics characteristics and treatment performance. These models enable particle classification, source identification, and prediction of removal efficiency across treatment stages. The framework (Fig. 1) emphasizes the importance of data preprocessing, feature extraction, and model validation to

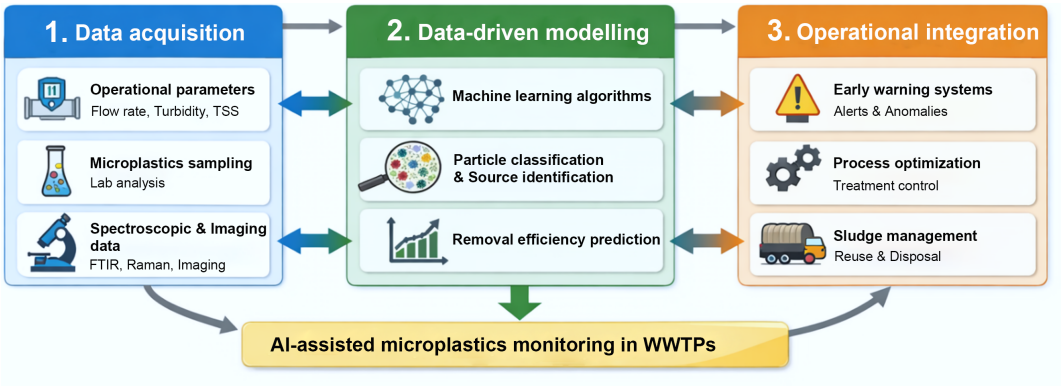


Fig. 1 Conceptual framework for AI-assisted microplastics monitoring and management in WWTPs.

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ensure reliable predictions. In the third component, model outputs are integrated into operational decision-making processes. AI predictions can support early warning systems, optimization of treatment processes, and improved sludge management strategies. This integration allows the transition from conventional monitoring approaches toward predictive and data-driven management of microplastics in WWTPs. Overall, the proposed framework provides a structured approach for linking microplastics monitoring with AI-based analysis and operational control, highlighting key steps required for the implementation of intelligent wastewater treatment systems.

Table 1 provides a mapping of the reviewed literature onto the three interrelated components of the proposed conceptual framework in Figure 1, namely data acquisition, data-driven modeling, and operational integration. Most of the studies published between 2019 and 2026 are primarily focused on data acquisition and analytical characterization of microplastics in wastewater systems through sampling, spectroscopic analysis, and morphological identification techniques. AI and machine-learning approaches are playing an increasing role in automated particle classification, predictive modeling, and treatment-performance assessment. However, the comparison also shows that relatively few studies have progressed toward full operational integration of AI-assisted systems in real WWTPs. Significant gaps remain, particularly regarding real-time monitoring, standardized datasets, large-scale validation of predictive models, and integration of AI outputs into operational decision-support systems. The reviewed literature suggests that current research is gradually shifting from conventional descriptive monitoring toward more integrated and predictive frameworks for intelligent wastewater management.

Microplastics in WWTPs

WWTPs are recognized as major pathways for the transmission of microplastics from human activities to aquatic and terrestrial ecosystems[43, 51]. Conventional WWTPs, although not specifically

Table 1 Mapping of reviewed literature onto the proposed conceptual framework for microplastics monitoring and management in WWTPs.

Framework component	Sub-component	Representative study	WWTP stage/application	Main methodology/ AI tool	Key finding and contribution	Remaining gap/limitation
Data acquisition	Influent, effluent and sludge monitoring	[43–45]	Monitoring of influent wastewater, treated effluent and sewage sludge during plant operation	Sampling, filtration, density separation	The studies showed that microplastics are consistently detected in all treatment streams, while large quantities accumulate in sewage sludge	Monitoring approaches still differ considerably between studies
Data acquisition	Morphological characterization	[43, 46]	Observation and characterization of particles recovered from wastewater samples	Optical microscopy and morphology analysis	Fibers and fragments appeared as the most common particle forms in WWTPs	Small particles are often difficult to separate from non-plastic material
Data acquisition	Spectroscopic polymer identification	[45, 47, 48]	Chemical identification of polymers detected in wastewater and sludge samples	FTIR, μ-FTIR, Raman spectroscopy	Spectroscopic techniques improved the reliability of polymer identification	High equipment cost and long analysis time limit routine use
Data acquisition	Sample pre-treatment and recovery	[49, 50]	Sample preparation prior to laboratory analysis of wastewater and sludge	Wet peroxide oxidation, enzymatic digestion, electrostatic separation	Pre-treatment methods improved particle recovery and reduced organic interference	Considerable methodological variation still exists between studies
Data-driven modeling	Automated image-based classification	[48, 51]	Automated recognition and classification of microplastics in monitoring workflows	Computer vision, Convolutional Neural Networks, ML classification	AI-based image analysis reduced manual work and achieved high classification accuracy	Model reliability under real environmental conditions still requires validation
Data-driven modeling	Predictive modeling for treatment optimization	[52]	Prediction of removal performance during coagulation and flocculation treatment	ANN, LSSVM, PSO-ANFIS, RBF models	Predictive models successfully estimated treatment performance under different conditions	Most models have only been tested at laboratory scale
Data-driven modeling	Cross-study statistical assessment	[53, 54]	Comparative evaluation of microplastics removal in different wastewater-treatment configurations	Statistical analysis and meta-analysis	The analyses identified operational factors influencing removal efficiency	Large operational datasets linked with AI applications remain limited
Data-driven modeling	AI-supported forecasting	[16–18]	Forecasting of wastewater quality trends and treatment behavior	Environmental machine-learning models	AI methods demonstrated strong potential for wastewater monitoring and prediction	Applications specifically focused on microplastics remain relatively limited
Operational integration	Treatment-process optimization	[54–56]	Evaluation and optimization of removal performance across treatment stages	Comparative process-performance analysis	Removal efficiency varied considerably depending on treatment configuration	Real-time operational optimization is still uncommon
Operational integration	Membrane and advanced treatment integration	[47, 57]	Application of membrane-based tertiary treatment systems for enhanced microplastics removal	membrane bioreactors (MBR), MF and UF systems	Membrane technologies achieved very high removal efficiencies in several studies	Fouling problems and operational cost remain important challenges
Operational integration	Sludge-management assessment	[43, 47, 55]	Investigation of microplastics accumulation and transfer during sludge treatment and disposal	Sludge accumulation and polymer distribution analysis	The studies confirmed that wastewater treatment transfers retained particles into sewage sludge	The long-term environmental behavior of sludge-associated microplastics is still unclear
Operational integration	Intelligent WWTP management and decision support	[48, 51]	AI-assisted monitoring and decision-support applications in WWTPs	AI-assisted monitoring systems	The studies indicate a transition toward AI-assisted wastewater management	Fully integrated AI-based operational platforms are still at an early stage of development

designed for microplastics elimination, accomplish substantial incidental removal throughout multiple treatment phases, leading to significant overall retention[44, 47]. Although high removal efficiencies are attained, the large volumes of treated wastewater render WWTPs considerable sources of microplastics emissions, potentially discharging millions of particles daily[51]. A thorough understanding of the origins, properties, prevalence, and behavior of microplastics in WWTPs is essential for accurately assessing their ecological impacts and identifying opportunities for improved monitoring, removal, and management strategies[43, 44].

Sources and characteristics of microplastics

Microplastics are typically defined as plastic particles less than 5 mm and are commonly present in WWTPs, notably in the influent, effluent, and sludge streams[43, 44, 57]. Due to their occurrence over a wide size range and with diverse origins, several classification schemes have emerged in the literature. Most studies classify microplastics into two groups: primary and secondary, based on their source. Primary microplastics are produced in microscopic sizes for industrial and commercial applications, whereas secondary microplastics are produced from the breakdown and progressive degradation of larger plastic materials in the environment[43, 44, 54]. Primary microplastics are most commonly in the form of microbeads in personal care products and industrial scrubbers. Secondary microplastics, on the other hand, are produced as a result of weathering processes acting on plastic debris in the environment over time. Environmental factors such as ultraviolet radiation, photolysis, hydrolytic degradation, mechanical abrasion, and biodegradation may all contribute to the degradation and fragmentation of plastic waste[43–45, 54]. There are currently various analytical methods used for identifying and characterizing microplastics in wastewater systems. Particle visualization and preliminary characterization are still one of the most used techniques by optical microscopy, while microfiltration (MF) techniques can allow the separation of particles smaller than 1 μm depending on the analytical configuration used[46]. In addition to source-based classification, microplastics can be classified based on their physical morphology. The most frequently reported forms in wastewater-treatment environments are fibers, fragments, pellets, films, foams, and microbeads[46].

Occurrence in influent and effluent streams

Microplastics are widely detected in WWTP influent and effluent worldwide[43, 44]. Reported influent concentrations range from 0.4 to 2,473 particles/L, while effluent concentrations range from 0.05 to 994 particles/L, reflecting substantial variability among treatment plants and regions[44]. Removal efficiencies vary widely between WWTPs. In some facilities in Iran and the United States, removal efficiencies above 90% have been reported. On the other hand, plants in Turkey achieved lower removal rates, around 48%[44]. Intermediate performance has also been observed in other regions. Two Moroccan WWTPs, for instance, reported removal efficiencies of 74% and 87%, respectively[44]. When results from several studies are considered together, secondary treatment systems remove on average about 88% of microplastics, while tertiary treatment processes can reach removal efficiencies close to 94%. A significant fraction of particles is already removed during the earlier stages of treatment, with preliminary and primary processes accounting for approximately 72% removal[43].

Differences in removal efficiency have often been linked to the configuration of the treatment process. Factors such as the presence of tertiary treatment units or MBR systems can influence performance. In addition, influent characteristics and operational conditions may also affect the overall removal efficiency[43, 44]. Reported weighted response ratio (RR) values differed across wastewater treatment technologies and treatment stages, indicating variable microplastics removal performance. Specifically, RR values were reported as 0.32 for biofilters, 0.33 for filtration systems, 0.39 for primary settling, 0.41 for biological reactors excluding A2/O and biofilters, 0.61 for grit and grease removal, and 0.73 for A2/O systems. Additionally, a field study indicated that 69–79% of microplastics entering WWTPs may already be removed during screening and grit removal processes[53].

At the process level, textile-industry WWTPs have demonstrated total removal efficiencies of 99% based on particle number but only 67.7% based on mass, indicating preferential retention of larger or heavier polymers[55]. Despite these high percentage removals, WWTPs can still emit several million microplastic particles per day because of the massive volumes of treated effluent, reinforcing their role as continuous point sources[51]. WWTP effluents are discharged into rivers, freshwater systems, and coastal waters, constituting an important pathway for microplastics to enter aquatic environments[43]. Consistent with influent patterns, fibers and fragments dominate effluent samples in most regions[44]. Fragments accounted for 66.7% of detected particles in municipal effluents in Greece[45].

Despite the large number of studies reporting microplastic concentrations in WWTP influent and effluent, significant inconsistencies remain across the literature. Reported concentration ranges vary by several orders of magnitude, which cannot be attributed solely to differences in wastewater composition. Instead, methodological variability, including differences in sampling strategies, particle size thresholds, and analytical techniques, plays a critical role in shaping reported values. Moreover, many studies rely on limited temporal datasets, which may not capture fluctuations in microplastics loads associated with seasonal variability or operational changes. As a result, direct comparison between studies is often challenging, and the reliability of global assessments remains uncertain. These limitations highlight the need for standardized monitoring protocols and more consistent reporting frameworks in future research.

Fate and accumulation during wastewater treatment

The efficiency of removal significantly differs among treatment stages in wastewater treatment facilities. Preliminary and primary processes collectively eliminate approximately 72% of microplastics from influent wastewater. The secondary and tertiary treatment stages attain average removal efficiencies of approximately 88% and 94%, respectively. Spherical particles ranging from approximately 27 to 179 μm are preferentially eliminated during primary sedimentation, contingent upon polymer characteristics[43]. Nonetheless, even tertiary-treated effluents can still represent substantial sources due to the extensive volumes consistently released[43, 47]. Larger plastic particles, including pellets, granules, and films, are frequently diminished during wastewater treatment procedures. Conversely, smaller fibers and fragments often endure and remain identifiable in treated effluents[44]. The majority of microplastics identified in municipal effluents fall within size categories under 250 μm. Particles exceeding 1,000 μm constitute merely 5.5–10.4% of the total[45]. Mechanical stress in treatment units can fracture plastics into smaller secondary microplastics[50]. Literature syntheses indicate that various treatment processes may facilitate particle fragmentation[58]. This fragmentation enhances the relative prevalence of smaller particles that are more challenging to retain. Particles smaller than 150 μm pose significant challenges for removal during primary clarification[43]. Size distribution

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analyses indicate that microplastic particles smaller than 1 mm dominate both influent and effluent streams. These particles account for approximately 65.0–86.9% of those detected in influent samples and 81.0–91.0% in effluent samples[56]. Similar patterns have been reported in field observations from a municipal WWTP in Ioannina. Sludge samples from this facility contained around 33.3 ± 8 microplastic particles/gram[45]. Among the detected particles, fragments were the most prevalent, representing about 75% of those found in sludge and roughly 66.7% of the microplastics identified in treated effluent. Fibers accounted for approximately 15 ± 5.9% of particles in municipal effluents, while spheres and films were detected only in relatively small quantities across the samples[45]. Fibers constituted approximately 15 ± 5.9% of particles in municipal effluents. Spheres and films were observed solely in diminished quantities throughout the samples. Polymer analysis identified polyamide, p-acrylic acid, and p-acrylamide-co-p-acrylic acid in all examined samples[45]. Additional polymers such as polyvinyl chloride, poly(butyl methacrylate) polyethylene, polystyrene, polypropylene, and polyvinyl alcohol exhibited detection frequencies ranging from 20% to 80%. Discrepancies noted across studies are frequently ascribed to methodological variability in analytical techniques[43, 44]. Detection limits, particle size thresholds, and polymer identification techniques significantly affect the reported removal efficiencies. The density of polymers significantly influences the partitioning behavior of microplastics. Low-density polymers typically remain suspended in the aqueous phase, whereas polymers with higher density tend to settle and accumulate within sludge fractions[43, 44]. As a result, WWTPs act as an important barrier that limits the release of microplastics into the environment[51]. Treated effluents are discharged into rivers and other freshwater bodies, which may subsequently transport microplastics to marine and coastal ecosystems[43].

Factors affecting microplastics transport and retention in WWTPs

Microplastics transport in WWTPs depends on particle properties[43]. These properties include particle size, shape, density, and polymer type. Particle size strongly influences microplastics removal efficiency. Larger particles are more readily retained during screening, grit removal, and sedimentation processes within treatment systems. In contrast, smaller particles, especially those below approximately 150 μm, often remain suspended and pass through treatment units[43, 47]. Polymer density also influences microplastics behavior within treatment systems[43]. Low-density polymers tend to remain suspended within the aqueous phase. Higher-density polymers more readily settle or associate with solids during treatment[43, 44]. Particle morphology additionally affects transport and retention behavior. Fibers often display different settling and entrapment dynamics compared with fragments, films, or pellets due to their elongated shape and higher tendency to remain suspended in flowing wastewater[44, 56]. Operational conditions within WWTPs further determine microplastics fate[43]. Treatment configuration strongly influences microplastics retention efficiency. Preliminary and primary stages already remove a substantial proportion of incoming particles. Secondary and tertiary stages enhance microplastics capture in wastewater treatment systems[43, 59]. These processes operate through mechanisms including sedimentation, flocculation, filtration, and membrane separation. Biological treatment also contributes substantially to the overall removal of microplastics. During activated sludge treatment, microplastics can become incorporated into sludge flocs[43, 47]. This incorporation facilitates the transfer of particles from the aqueous phase into sewage sludge. As a result, many retained microplastics accumulate in sludge rather than remaining in treated effluent. However, sludge recirculation may redistribute some retained particles back into the treatment process. This internal recycling can influence the transport and distribution of microplastics within the plant[53].

Recent studies emphasize the importance of broader operational drivers affecting removal performance[51, 54]. Wastewater type and the configuration of secondary treatment systems have been identified as statistically significant factors influencing microplastics retention. Additional operational parameters, including process conditions and plant management practices, can also contribute to variations in removal efficiency. Consequently, the effectiveness of microplastics removal depends not only on particle characteristics but also strongly on treatment plant design and operational conditions[51, 54].

Detection and quantification of microplastics

Reliable detection and quantification of microplastics in environmental wastewater samples require a multi-step analytical workflow. This workflow typically involves sample collection, pre-treatment to remove organic and inorganic matter, particle separation using filtration or density-based techniques, and final identification through microscopic or spectroscopic methods[43, 47]. Because microplastics occur in a wide range of sizes, shapes, and polymer types, no single analytical technique can provide a complete characterization. For this reason, many studies combine visual examination with chemical identification techniques such as Fourier transform infrared spectroscopy or Raman spectroscopy to confirm polymer composition and reduce the risk of misclassification[48]. The main AI-assisted analytical and operational applications discussed in this section are summarized in Figure 2.

Experimental procedures used for sampling, analysis, and quantification vary considerably among studies, which contributes to the large variability observed in reported microplastic concentrations[43]. Visual identification and spectroscopic techniques are widely used in microplastics research. Despite their widespread application, these analytical methods have several limitations[47, 48]. They are often labor-intensive, time-consuming, and susceptible to operator bias. In addition, preliminary visual sorting prior to spectroscopic verification can lead to classification errors. Such misclassification is particularly common for smaller particles during manual identification procedures. Reported error rates range from 20% to 70%, depending strongly on particle size[43]. Vibrational spectroscopy techniques are widely used for reliable polymer identification. Commonly applied methods include FTIR and Raman spectroscopy for chemical characterization of plastics. However, these analytical techniques usually require careful sample preparation and relatively long analysis times[48]. Raman spectroscopy can detect extremely small microplastic particles. It is capable of identifying particles smaller than 20 μm and even approaching sizes around 500 nm. This capability makes Raman particularly valuable for analyzing very fine particle fractions. Such small particles are often difficult to identify using conventional visual inspection methods. Nevertheless, Raman spectroscopy also presents several analytical challenges during microplastics analysis. Fluorescent compounds can interfere with spectral signals during measurement. In addition, overlapping spectra between polymers may complicate chemical identification. Photodegradation of plastic particles may also occur during Raman analysis. Furthermore, analysis time may increase when manual spot selection is required during spectral acquisition procedures[48].

In recent years, AI and ML are increasingly used in microplastics analysis. These technologies improve automated particle

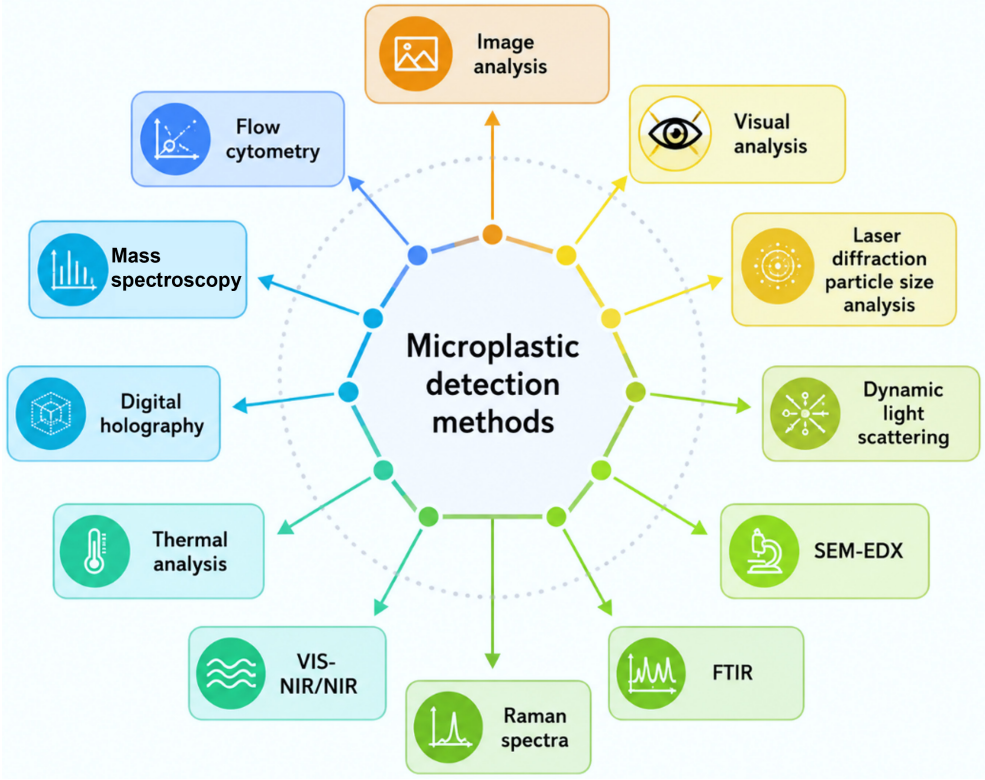

Fig. 2 Overview of detection techniques.

identification and classification accuracy[48, 51]. In particular, computer vision techniques combined with ML algorithms have been proposed to reduce subjectivity in visual analysis and to support automated feature extraction for real-time monitoring and classification of microplastic particles[48]. Several recent studies have reported classification accuracies exceeding 85–95% when convolutional neural networks and image-based machine-learning approaches were applied for automated microplastics detection under controlled experimental conditions[48]. In addition to improving classification consistency, automated image analysis may considerably reduce the time required for particle identification compared with conventional manual microscopic analysis.

Sampling and pre-treatment methods

Sampling strategies in WWTPs typically involve collecting samples from influent, effluent, and sludge in order to assess the presence and distribution of microplastics across the different stages of treatment[50]. However, these sampling approaches are not yet standardized. As a result, considerable variability exists in both sampling design and the particle size ranges that are included in different studies. For example, in the 21 WWTP investigations reviewed by Iyare et al. (2020)[43], the size of the sampled particles varied widely, ranging from as small as 1–10 μm to several millimeters. This highlights the methodological heterogeneity that still characterizes microplastics research[43].

After collection, samples usually undergo filtration or sieving before further analysis. The mesh sizes used during this step can differ substantially between studies. Reported values range from approximately 10 μm to more than 500 μm, and this variation directly influences the lower detection limit and, consequently, the reported abundance of microplastics[43, 50]. In addition to mechanical separation methods, density separation is commonly applied to isolate plastic particles from heavier inorganic materials. Chemical digestion is also frequently used in order to remove organic matter that may interfere with subsequent analysis[50].

Because microplastics are often present at relatively low concentrations, contamination during sampling and laboratory processing can significantly influence the results. For this reason, strict contamination control procedures are repeatedly emphasized as essential for producing reliable datasets[47]. In recent years, several alternative pre-treatment approaches have also been proposed. One example is a method based on electrostatic behavior, which can separate microplastics from environmental matrices while removing up to 99% of the original sample mass without losing plastic particles[49]. Using a modified electrostatic metal/plastic separator, nearly 100% recovery was reported in spiked matrices such as quartz sand, freshwater suspended particulate matter, freshwater sediment, and beach samples[49].

Different preparation techniques may also be applied depending on the sample type. For instance, wet peroxide oxidation using 30% H_2O_2 in the presence of ferrous iron has been used for effluent samples. In contrast, sludge samples often require more complex treatment, such as a combination of enzymatic digestion and wet peroxide oxidation[45]. Despite these methodological developments, important differences in sample preparation procedures still remain between studies. Variations in digestion protocols and density separation steps are considered one of the main reasons for the inconsistencies observed in reported microplastic concentrations[43, 44]. Consequently, careful sampling design, together with strict contamination control, remains essential for ensuring reliable and comparable microplastics data[50].

Conventional analytical techniques

Following sample pre-treatment, microplastics identification typically relies on a combination of visual and spectroscopic analytical

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techniques. Optical microscopy is commonly used as an initial step for the preliminary identification and morphological characterization of suspected particles[47]. Using this approach, particles are classified according to observable characteristics such as size, shape, and color. However, visual identification largely depends on operator experience and judgment, and visual counting may therefore be affected by inter-operator variability, with reported differences of up to 30% between analysts[48]. These limitations become more pronounced when analyzing smaller particles, particularly those in the 10–30 μm size range, which can be difficult to distinguish from natural or synthetic non-plastic materials. Consequently, such particles are often classified as "potential" microplastics until chemical confirmation is performed[43].

To improve identification accuracy, spectroscopic techniques are widely applied for polymer characterization. FTIR spectroscopy is among the most frequently used methods for polymer identification in WWTP studies, while micro-FTIR enables the analysis of smaller particles with improved spatial resolution[43, 47]. Raman spectroscopy is also widely employed for chemical characterization because it offers high spatial resolution and the ability to detect relatively small particles[47]. In addition, pyrolysis-gas chromatography/mass spectrometry (Py-GC/MS) is used for polymer identification and mass-based quantification, providing complementary information to particle-based analytical approaches[47]. More recently, micro-Raman spectroscopy combined with specialized software has been applied to detect and quantify microplastics in WWTP effluent and sludge samples[45].

Comparative assessments of conventional analytical techniques indicate that FTIR spectroscopy is polymer-specific and non-destructive; however, its performance may be limited for particles smaller than approximately 10 μm and may also be influenced by colored microplastics. Raman spectroscopy, by contrast, provides higher spatial resolution and enables the detection of smaller particles, although its performance can be affected by fluorescence interference and longer analysis times associated with spectral mapping[48]. Other analytical techniques are also applied in microplastics research. For example, scanning electron microscopy coupled with energy-dispersive X-ray spectroscopy enables high-resolution imaging of particle surface morphology but requires vacuum conditions and complex sample preparation. Mass spectrometry-based techniques such as Py-GC/MS provide accurate chemical profiling of polymer composition; however, they are destructive methods and do not preserve information about particle morphology[48].

Comparative evaluation of analytical techniques for microplastics detection in wastewater systems

The selection of an appropriate analytical technique for microplastics detection depends not only on analytical accuracy but also on practical considerations. In WWTPs, monitoring activities are often performed under operational constraints, including limited analytical infrastructure, restricted budgets, and the need for relatively rapid results. Consequently, the practical applicability of analytical methods becomes a key factor in method selection. Table 2 summarizes commonly used techniques for microplastics identification and compares their principal technical characteristics together with their operational advantages and limitations for wastewater monitoring. Optical microscopy remains one of the most accessible tools for detecting microplastics in wastewater studies. The method requires relatively simple laboratory equipment and can be implemented in many environmental laboratories without highly specialized instrumentation. For this reason, it is frequently applied for preliminary screening of wastewater samples. From an operational perspective, microscopy provides a rapid estimate of particle abundance and basic morphological characteristics. However, visual identification alone cannot reliably confirm polymer composition. The approach also depends strongly on operator expertise, and distinguishing synthetic fibers from natural materials can be challenging. As a result, microscopy is generally used as an initial screening step prior to spectroscopic confirmation[43, 47]. FTIR spectroscopy is widely applied to confirm the chemical composition of suspected microplastic particles. One of its principal advantages is the ability to identify polymer types in a non-destructive manner. Such information can assist in identifying potential sources of microplastics entering wastewater systems. For instance, the detection of polymers such as polyethylene, polypropylene, or polyester fibers may indicate inputs from packaging materials or textile-related sources. Nevertheless, FTIR instrumentation requires specialized equipment and trained personnel, meaning that routine analyses may need to be conducted in specialized laboratories. In addition, detecting very small particles can be challenging, particularly for particles smaller than approximately 10–20 μm[43, 47, 48]. Raman spectroscopy provides higher spatial resolution than FTIR and therefore enables the detection of smaller microplastic particles. This capability allows more detailed characterization of fine particle fractions that may escape conventional treatment processes. Although this makes Raman spectroscopy particularly valuable for research applications, it is less commonly applied in routine monitoring programs. The instrumentation is expensive and the analysis can become time-consuming when samples contain large numbers of particles. Furthermore, fluorescence originating from organic matter can interfere with Raman signals in environmental samples[45, 48]. Pyrolysis-GC/MS represents an alternative analytical strategy for microplastics identification[47, 48]. Instead of examining individual particles, this method determines the overall polymer composition of a sample. The technique thermally decomposes plastic materials and subsequently analyzes the resulting chemical fragments. As a result, accurate mass-based quantification of polymer types within complex environmental matrices can be achieved. This approach is particularly useful for sludge samples, where isolating individual particles may be difficult. However, the method is destructive and therefore does not preserve information regarding particle morphology or size following analysis[47, 48]. More recently, automated microscopy systems supported by ML have been proposed for microplastics identification[48, 51]. These systems analyze digital images to detect and classify particles according to morphological characteristics such as shape, elongation, or surface texture patterns. Their primary advantage is the potential reduction of operator bias together with faster processing of large image datasets. Nevertheless, the reliability of these approaches depends strongly on the quality and representativeness of datasets used during model training. Consequently, their practical implementation in many wastewater laboratories remains at an early stage[48, 51]. Overall, selecting analytical techniques requires balancing analytical accuracy, cost, and operational feasibility. For this reason, many wastewater monitoring studies apply combined analytical workflows that typically include filtration, visual screening, and spectroscopic confirmation of suspected particles. Future monitoring strategies may increasingly integrate automated image analysis together with improved spectroscopic techniques, which could enhance both analytical efficiency and the reliability of microplastics monitoring data.

AI-assisted traceability and source identification of microplastics

Research on microplastics in wastewater systems has gradually moved beyond simple detection and quantification. More recent studies also attempt to understand where these particles originate from, how they move through treatment units, and in which parts of the system they

Table 2 Analytical techniques used for microplastics detection and quantification in wastewater samples.

Technique	Analytical principle	Typical particle size detection	Sample preparation requirement	Output type	Analysis time	Main advantage	Main limitation	Reference
Optical microscopy	Visual identification of particles based on morphology (size, color, shape)	20 μm–5 mm	Filtration/sieving followed by visual sorting	Particle count and morphology	Low-moderate	Simple and inexpensive method widely used for preliminary screening	High operator bias and potential misidentification, particularly for small particles	[43, 47]
FTIR spectroscopy (μ-FTIR)	Infrared absorption spectra used to identify polymer chemical bonds	10–20 μm	Filtration, organic matter digestion and particle isolation	Polymer identification (particle-based)	Moderate	Non-destructive method widely used for polymer identification in environmental samples	Limited spatial resolution for very small particles and interference from colored plastics	[43, 47, 48]
Raman spectroscopy	Laser-based vibrational spectroscopy detecting molecular fingerprints	<20 μm (down to 500 nm)	Filtration and particle isolation; minimal chemical preparation	Polymer identification (particle-based)	High	High spatial resolution enabling identification of very small particles	Fluorescence interference and longer analysis time due to spectral mapping	[45, 48]
Electron microscopy coupled with energy-dispersive X-ray spectroscopy	Electron microscopy with elemental analysis for surface characterization	1–10 μm	Drying and vacuum preparation of samples	Morphological and elemental composition	High	Provides detailed surface morphology and structural characterization	Expensive instrumentation and complex sample preparation	[48]
Pyrolysis-GC/MS	Thermal degradation of polymers followed by chromatographic separation and mass spectrometry	Not size-dependent	Chemical digestion and isolation of organic matter	Mass-based polymer composition	High	Highly accurate polymer identification and quantitative mass determination	Destructive technique without particle size or morphology information	[47, 48]
Fluorescence microscopy	Detection of stained microplastics using fluorescent dyes (e.g., Nile Red)	10–100 μm	Staining and filtration of samples	Particle count	Low-moderate	Rapid detection and suitable for high-throughput screening	Potential interference from natural organic matter	[48]
Computer vision + ML	Automated classification of microplastics using image analysis algorithms	Method-dependent	Microscopy imaging followed by dataset training	Particle classification and counting	Low once trained	Reduces operator bias and enables automated analysis	Requires large training datasets and validation	[48, 51]

finally accumulate. To support this type of analysis, AI and data-driven methods are increasingly being explored for microplastics traceability in WWTPs. These approaches usually combine several different types of information, including particle morphology, polymer composition, operational conditions, and monitoring data collected from different treatment stages. Machine-learning techniques such as convolutional neural networks, random forest (RF), and support vector machines have been applied for particle classification based on color, shape, texture, and polymer type. In this way, it may become easier to distinguish textile fibers, industrial plastic fragments, packaging-derived particles, and materials associated with urban runoff.

Recent studies have explored the combined application of spectroscopic analysis, image processing, and statistical modeling for the investigation of microplastics transport and source identification in wastewater systems[48, 51]. Automated image-analysis techniques are increasingly used because manual particle classification often becomes difficult when wastewater samples contain large numbers of heterogeneous particles. In parallel, predictive modeling approaches have been applied to better examine transport pathways and retention behavior during treatment processes. Some researchers have additionally linked operational parameters, including flow rate, suspended solids concentration, and sludge recirculation, with particle-characterization datasets to obtain a clearer understanding of microplastics distribution patterns within WWTPs.

Recent studies have investigated possible correlations between routinely monitored wastewater parameters and microplastic concentrations in treatment systems. The correlations reported between total suspended solids, turbidity, and microplastics abundance varied considerably between studies and operational conditions[60]. In many cases, the observed relationships were strongly influenced by wastewater composition. Treatment configuration, influent variability, particle morphology, and dominant polymer types may also considerably affect the strength and reliability of these correlations during monitoring activities. Their predictive capability often becomes weaker under unstable operating conditions. This is particularly evident during stormwater inflow events or rapid changes in particle-size distributions within wastewater streams. At the same time, turbidity and total suspended solids are not exclusively associated with microplastic particles. Organic matter and non-plastic suspended solids may also contribute significantly to these measurements, making interpretation more difficult during practical wastewater monitoring. Consequently, although surrogate operational parameters may support rapid preliminary assessment, their application in AI-assisted monitoring systems still requires site-specific calibration, external validation, and comparison with direct analytical measurements before reliable operational implementation can be achieved.

AI-assisted monitoring methods are increasingly explored in wastewater microplastics research. Still, several important limitations continue to affect their reliability and wider practical applicability. Many currently available machine-learning models are trained using relatively small laboratory datasets generated under controlled experimental conditions. Although several studies presented in Table 3 report high predictive performance and classification accuracies, these results may not always reflect real wastewater treatment conditions, where model performance can decline because of operational variability and dataset complexity. Another important limitation involves the lack of external validation across different WWTPs. Wastewater composition, influent characteristics, operational parameters, and treatment configurations frequently

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vary between facilities, potentially influencing prediction accuracy and reducing model transferability under different environmental and operational conditions. Several image-based studies also rely on simplified datasets collected under controlled lighting, imaging, and sample-preparation procedures. Real wastewater matrices are substantially more heterogeneous and commonly contain suspended solids, organic matter, and overlapping particle characteristics that complicate particle recognition and classification during practical implementation. In addition, methodological differences between studies, including analytical workflows, particle-size thresholds, and spectroscopic procedures, continue to affect dataset consistency and the development of robust AI-based monitoring models. Overall, AI-assisted systems may improve microplastics detection and wastewater-process optimization in WWTPs. However, broader validation using larger and more representative datasets remains necessary before reliable large-scale implementation can be realistically achieved.

Removal of microplastics in WWTPs

Microplastics are removed in WWTPs through a combination of interconnected processes taking place along the treatment train, rather than through a single mechanism. Physical separation, biological interactions, and physicochemical processes all play a role in their retention, with removal typically resulting from screening, sedimentation, biological flocculation, and tertiary polishing acting together. The efficiency of these processes varies considerably and is strongly affected by particle characteristics such as size, density, shape, and polymer type, with particle size often being the most influential factor. Conventional WWTPs can remove a proportion of incoming microplastics, but they are not specifically designed to retain very small particles, which explains why reported removal efficiencies vary widely, usually between 64–99% depending on plant configuration and treatment processes[44]. In practice, incomplete removal is mainly associated with particles smaller than about 150 μm, which are not effectively removed by sedimentation processes[43]. Since primary clarification relies on density-driven separation, removal efficiency depends on both particle size and polymer density, meaning that low-density plastics may remain suspended while smaller particles can pass through the system and be discharged with effluents[43, 44, 47]. Differences in removal efficiencies reported across countries largely reflect variations in plant design, operational conditions, influent composition, and even analytical methods used in different studies[43,44]. A typical WWTP includes preliminary, primary, and secondary stages, where screening and grit removal occur first, followed by sedimentation and then biological treatment, usually based on activated sludge systems[43]. Microplastics removal tends to increase progressively across these stages, with preliminary and primary treatment removing around 72% of particles and secondary treatment raising total removal to roughly 88%, while tertiary processes can further increase this to about 94%[43]. Activated sludge systems enhance removal by incorporating microplastics into biological flocs, which are then transferred to sludge, while primary sedimentation is particularly effective for larger particles in the range of 27–149 μm. Even so, smaller particles frequently remain in the treated effluent[43]. Although conventional systems significantly reduce microplastics loads, they do not achieve complete removal, and their performance is still closely linked to plant design and operational conditions. Tertiary treatments such as rapid sand filtration and gravity filtration can improve retention further, although their efficiency varies between systems[44]. A meta-analysis has shown that filter-based technologies, including biofilters, ultrafiltration, and rapid sand filters, generally achieve strong removal performance, while sequencing batch reactors can reach up to 98% removal under certain conditions, whereas some biological systems such as A/O processes show much lower retention, around 16.9%[56]. To address these limitations, more advanced technologies are increasingly being explored, particularly membrane-based systems such as MBRs, which combine biological treatment with membrane filtration and allow effective retention of suspended solids and microplastics within the reactor[47]. Membranes such as MF and UF are commonly applied in tertiary stages and often achieve removal efficiencies above 95% for particles larger than their pore size, while additional filtration steps, including sand filters and disc filters, can further reduce concentrations after secondary treatment[43]. These systems generally outperform conventional processes because of their smaller pore sizes, although issues such as membrane fouling, higher operational complexity, and increased costs still limit their wider application[57]. Chemical and physicochemical methods also contribute to removal, with coagulation-flocculation promoting particle aggregation and electrocoagulation emerging as a promising

Table 3 Technologies for microplastics removal in wastewater treatment (evidence reported in 2016–2026 literature).

Technology category	Representative processes/units	Main removal mechanism	Typical performance/remark	Reference
Conventional treatment processes	Screening, grit removal, primary sedimentation, activated sludge, tertiary polishing	Physical settling and capture of microplastics within sludge flocs during biological treatment	Removal efficiencies may reach 88–94%, although smaller particles (<150 μm) can still escape treatment.	[43, 44, 47]
Filter-based technologies	Rapid sand filters (RSF), DFs, biofilters, gravity filtration	Physical straining and retention of particles within filter media	Commonly applied as tertiary polishing steps; performance depends on filter properties and operational conditions.	[43, 47, 56]
MBR	MBRs, MF, UF membranes	Size-exclusion and physical retention through membrane pores	Membrane systems may achieve removal efficiencies above 95% by retaining fine particles.	[47, 57]
Chemical and physicochemical processes	Coagulation-flocculation, coagulation-sedimentation, electrocoagulation	Aggregation of particles into larger flocs that can be removed by sedimentation or filtration	Enhances particle aggregation and settling; efficiency depends on wastewater characteristics and coagulant dosage.	[47, 52, 55]
Advanced oxidation processes	UV, O_3, UV/O_3 systems	Oxidative transformation and degradation of polymer structures	May fragment or modify microplastics rather than fully remove them.	[53, 61]
Flotation-based separation	Mechanical flotation, column flotation, nanobubble-assisted flotation	Density-based separation and attachment of particles to air bubbles	Promising removal efficiencies reported in laboratory and pilot-scale studies.	[62]
Biological and hybrid systems	Activated sludge capture, BAF, combined physico-chemical-biological processes	Physical entrapment of microplastics within sludge flocs and biological aggregates	A large fraction of retained microplastics accumulates in sewage sludge.	[43, 47]
Meta-analytic and data-driven assessments	Cross-technology comparisons, statistical analyses of WWTP performance	Data-driven analysis of treatment performance across different WWTP configurations	Useful for identifying operational factors influencing removal efficiency.	[53, 54]

alternative[47, 52]. Advanced oxidation processes can alter or degrade plastic particles, although they may also lead to fragmentation into smaller particles, which makes removal assessment more challenging[53, 61]. In addition, machine-learning-based models such as ANN, LSSVM, PSO-ANFIS, and RBF have been applied to optimize coagulation processes, with RBF models showing high predictive performance (R^2 = 0.96)[52] while coagulation-sedimentation has demonstrated particularly high removal efficiency for specific polymers such as PET[55]. Biological treatment mainly contributes through the capture and accumulation of microplastics within activated sludge, as microbial degradation remains limited under conventional conditions, which is why hybrid physicochemical-biological approaches are now being explored to enhance removal efficiency (Haq and Shah, 2025). Evidence from textile WWTPs also highlights strong process-dependent differences, with hydrolysis-acidification showing higher removal efficiency for certain polymers compared to aerobic treatment and filtration stages[55].

Across global studies, microplastics removal efficiency varies widely between countries and WWTP configurations[44]. In general, advanced treatment technologies tend to achieve higher removal efficiencies that conventional systems, although no single technology currently enables complete elimination of microplastics[47]

The technologies outlined in Table 3 vary in their mechanisms and operational requirements. Traditional treatment methods remain the main approach in most WWTPs, where screening, sedimentation, and biological treatment collectively retain a substantial proportion of incoming particles. Their efficacy is strongly influenced by particle size, density, and morphology. Particles smaller than approximately 150 μm often remain suspended and are discharged with treated effluents, highlighting a key limitation of conventional treatment configurations[43, 44, 47]. Filtration technologies are commonly applied as tertiary polishing processes to improve microplastics retention. Rapid sand filters and disc filters (DFs) capture particles through straining and interception within porous media. Their performance depends on hydraulic loading, filter media characteristics, and maintenance conditions[43, 47, 53]. Membrane-based systems generally achieve the highest removal efficiencies among existing technologies. MBRs and MF/UF membranes provide a physical barrier capable of retaining fine particles that bypass conventional sedimentation. Reported removal efficiencies often exceed 95%. However, their application is limited by membrane fouling, increased energy demand, and elevated operational costs[47, 57]. Physicochemical processes provide additional removal pathways. Coagulation-flocculation and electrocoagulation promote particle aggregation into larger flocs that can be removed through sedimentation or filtration. Their efficiency depends on coagulant type, dosage, and wastewater composition[47, 52, 55]. In contrast, advanced oxidation processes act through chemical transformation rather than physical separation. These processes may fragment plastics into smaller micro- or nanoplastic particles rather than completely removing them, complicating removal assessments[61, 63]. Flotation-based separation has emerged as an alternative approach that exploits density differences by attaching particles to rising air bubbles. Laboratory and pilot-scale studies report promising removal efficiencies; however, performance varies depending on polymer properties, particle hydrophobicity, and wastewater composition. Recent reviews also emphasize the need for standardized methodologies and improved scalability for integration into full-scale treatment systems[64]. Biological treatment contributes indirectly through the incorporation of microplastics into activated sludge flocs, which subsequently settle during clarification. As a result, a large fraction of retained microplastics accumulates in sewage sludge. While this reduces emissions to receiving waters, it raises concerns about the transfer of microplastics to terrestrial environments through sludge reuse[43, 47]. Comparative analyses indicate regional differences in removal performance, reflecting variations in infrastructure, operational practices, and technology adoption. Overall, no single technology ensures complete removal of microplastics from wastewater. Effective mitigation therefore requires the combined application of physical, biological, and physicochemical processes. Much of the retained microplastics ends up concentrated in sewage sludge. This limits the direct discharge into receiving waters, but the subsequent fate of sludge after its disposal or application to agricultural lands is unknown. Microplastics added to soils via sludge may persist in the environment for long periods of time, whereas some particles can slowly migrate through runoff or biological activity. It is still not fully understood how these particles persist in terrestrial systems over the long term and move through food webs. Therefore, wastewater treatment can reduce emissions to aquatic environments, but not completely eliminate the broader environmental burden that microplastics represent.

Meta-analyses further highlight that treatment configuration, operational conditions, and influent characteristics strongly influence removal efficiency[53, 54]. Despite relatively high reported removal efficiencies, complete elimination of microplastics is not achieved in practice. This limitation is primarily associated with the persistence of small particles, which are less effectively retained by both conventional and advanced treatment systems. In addition, reported efficiencies are strongly influenced by analytical methodologies and particle-size detection limits. In some cases, apparent increases in microplastic concentrations are observed due to fragmentation during treatment rather than actual removal failure. These findings indicate that current performance assessments may not fully reflect the true fate of microplastics within treatment systems and highlight the need for more consistent evaluation approaches.

AI for operational monitoring and management of microplastics in WWTPs

AI-assisted detection and data analysis

Conventional approaches for identifying microplastics are still largely labor-intensive and time-consuming, which is why there has been a clear shift towards automated solutions based on AI and ML[48]. Different ML approaches have been applied in microplastics research, each with specific advantages and limitations depending on the type of data and application. Traditional algorithms such as support vector machines and RF are widely used due to their robustness and relatively good performance with limited datasets[48, 51]. RF models are particularly effective for classification tasks and can handle complex, non-linear relationships, although they may lack interpretability[51]. Support vector machine models are suitable for high-dimensional data, such as spectral datasets, but their performance is sensitive to parameter selection and data scaling[48]. Deep learning methods, including convolutional neural networks, have shown strong potential for automated image-based microplastics detection and classification, achieving high accuracy when large annotated datasets are available[48]. However, they require significant computational resources and large training datasets, which are not always accessible in environmental studies. The applicability of each method therefore depends on the characteristics of the dataset and the specific research objective, with deep learning being more suitable for image-based analyses and traditional ML models for tabular operational data[51]. In practice, computer vision combined with ML algorithms makes it

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possible to detect and classify microplastic particles using morphological descriptors such as elongation, sphericity, and eccentricity, although performance can vary depending on image quality. The performance of AI-assisted image analysis is also influenced by the physicochemical properties of microplastic particles. Polymer density may affect particle behavior during sampling and imaging preparation, since low-density polymers tend to remain suspended, whereas denser polymers are more likely to settle or associate with sludge fractions. In addition, particle morphology strongly influences feature extraction in computer vision models. Fibers typically exhibit elongated and overlapping geometries, while fragments and pellets present more compact or angular shapes. These differences affect the extraction of descriptors such as aspect ratio, texture, edge features, and particle contour, which may influence classification accuracy. Smaller particles (<150 μm), which are already difficult to remove during conventional wastewater treatment, also present additional challenges for automated detection because of reduced image resolution and increased risk of misclassification. Consequently, robust AI-based monitoring systems require diverse and well-annotated training datasets that include variations in particle size, morphology, color, and polymer type in order to improve model generalization across different wastewater matrices. Deep learning has also been explored using photoacoustic imaging and VIS/NIR spectral data, with several studies reporting encouraging results when dealing with complex environmental samples. At the same time, automated image analysis, particularly when used together with RF classifiers, has been found to improve how stained microplastics are segmented and quantified in bottled water samples (Periyasamy & Perumalsamy, 2025). More recently, ML is not only used for identifying particles but also for understanding where they come from and how treatment systems perform, which makes these approaches more useful in practice. For example, multilabel decision tree, RF, and support vector machine models were applied in four WWTPs in Hong Kong to trace the main sources of microplastics[51], showing that domestic sources were the largest contributors (57.3–59.9%), followed by industrial sources (21.1–21.7%), domestic or medical activities (4.6–5.1%), and domestic or agricultural inputs (2.6–3.8%). The same study pointed out that what happens to microplastics during treatment does not depend only on how the plant operates, but also on the physicochemical characteristics of the particles themselves[51]. In a similar way, machine-learning-based partial least squares regression models have been used to estimate removal performance in WRRFs[54] where factors such as secondary treatment configuration and wastewater type were found to be statistically significant ($p < 0.01$). Still, ML-based classification of microplastics is quite sensitive to factors like data variability, sampling bias, and spectral noise, which can make models less reliable, especially when validation datasets are small or not very diverse[48]. Another challenge related to the application of AI in wastewater monitoring concerns the limited interpretability of many machine-learning models. Although complex algorithms such as deep neural networks and ensemble models can achieve high predictive performance, their internal decision-making processes are often difficult to interpret. This "black-box" characteristic may reduce confidence in AI-assisted decision-support systems, particularly in operational environments where model transparency is important for process control and management decisions. As a result, increasing attention is being given to explainable AI approaches such as shapley additive explanations (SHAP) values and local interpretable model-agnostic explanations (LIME), which can help identify the variables that most strongly influence model predictions. In addition, causal machine-learning approaches may provide further insight into the relationships between operational conditions and microplastic behavior in WWTPs. Improving model interpretability will likely be an important step toward the wider practical implementation of AI-assisted monitoring systems in wastewater treatment.

AI applications for microplastics monitoring in WWTPs

AI is increasingly acknowledged as a viable framework for improving microplastics monitoring and management in WWTPs. However, current monitoring strategies primarily rely on labor-intensive sampling techniques, laboratory-based particle identification, and sporadic datasets, significantly constraining plant operators' ability to assess microplastic dynamics in real time[43, 47, 48]. The behavior of microplastics in wastewater treatment facilities is further complicated by the considerable influence of particle characteristics, influent composition, and operational conditions. The interaction of these variables produces nonlinear transport and retention processes that are difficult to depict with traditional empirical or mechanistic modeling methods[44, 51, 56]. Recent studies suggest that surrogate indicators like suspended solids and turbidity may correlate with microplastic concentrations in wastewater, indicating that routinely collected plant data could facilitate proxy-based estimation strategies[60, 65]. Despite the promising nature of these correlations, their reliability across various WWTP configurations and operational conditions has not been adequately validated. Subsequent to data acquisition, preprocessing and feature extraction are typically necessary to transform raw monitoring data into structured datasets appropriate for machine-learning analysis, including descriptors such as particle size, morphology, polymer type, hydraulic retention time, sludge retention time, and treatment configuration. Recent studies of wastewater treatment facilities indicate that the physicochemical characteristics of particles and the operational conditions of the plants substantially affect the transport and retention dynamics of microplastics within these systems[51, 54, 55, 63]. AI-based methodologies offer a significant benefit by facilitating the concurrent analysis of diverse datasets that are usually assessed in isolation in traditional wastewater and microplastics studies. Diverse ML algorithms, such as artificial neural networks (ANN), support vector machines, random forest models, and decision trees, are extensively employed in wastewater engineering for process prediction, anomaly detection, and operational optimization[37, 39, 40, 62, 66]. Comparable methodologies are currently under development in microplastics research, wherein ML has been utilized for automated particle identification, quantification, and source analysis[48, 51, 67]. Notwithstanding these advancements, the amalgamation of AI with operational wastewater management is still in its nascent phase, with the majority of research predominantly concentrating on detection or classification rather than comprehensive process-scale forecasting of microplastics disposition. When adequately trained datasets are accessible, AI models can produce operationally pertinent predictions, encompassing assessments of influent microplastics loads, removal efficacy across treatment phases, and the allocation of particles between treated effluent and sewage sludge. These predictive capabilities could support plant management by enabling early detection of unusual influent conditions, anticipating microplastics accumulation in sludge, and improving the performance of treatment units. Ultimately, the main value of AI may lie not only in automating analysis but also in linking microplastics monitoring with predictive, data-driven management strategies. Such integration could help move wastewater treatment from descriptive assessment toward proactive control of microplastics pollution in advanced WWTP systems[68, 69].

Although AI-based approaches are gaining increasing attention, conventional instrumental techniques such as FTIR and Raman

spectroscopy are still more commonly used for microplastics identification in practice. This is mainly because they provide direct and reliable information on polymer composition, which is essential for both scientific analysis and regulatory applications. In contrast, ML models rely heavily on the availability and quality of training data. Environmental datasets are often limited, heterogeneous, and not consistently labeled, which can affect the accuracy and generalization of ML models when applied to different wastewater treatment systems. Furthermore, applying AI in full-scale WWTPs is not always straightforward, as it requires appropriate monitoring infrastructure, computational capacity, and technical expertise. On the other hand, instrumental methods, despite being time-consuming, are well-established, standardized, and widely accepted by the research community. For this reason, AI is currently better viewed as a complementary tool rather than a replacement for conventional techniques, helping to improve data analysis, enable faster screening, and support predictive monitoring.

AI for influent characterization and early warning of microplastics loads

Prompt identification of pollution incidents in WWTPs continues to pose a significant challenge. AI monitoring systems are increasingly investigated as tools to enhance operational oversight and enable the early detection of anomalous influent conditions in treatment facilities. Compared with conventional laboratory-based monitoring approaches, AI-assisted systems may support faster anomaly detection and near-real-time process evaluation through continuous sensor integration and automated data analysis. Although large-scale economic assessments remain limited, increased automation could reduce manual processing requirements and improve operational response times in WWTP monitoring applications. ML methodologies, such as ANN, support vector machines, and decision trees, are extensively used to forecast wastewater quality parameters and support monitoring through high-frequency sensor datasets[68]. These models can analyze continuous data to detect anomalies. Through the analysis of high-frequency monitoring data, they can identify anomalous patterns and predict influent characteristics, thus supporting operational decision-making in wastewater treatment systems[68]. Microplastics in wastewater often aggregate with suspended particles. This relationship indicates that frequently monitored parameters like turbidity and total suspended solids may serve as surrogate indicators for estimating microplastic concentrations in wastewater streams. Numerous studies have reported correlations among these variables. This evidence suggests that regularly monitored parameters could support cost-effective monitoring strategies for evaluating and tracking microplastic dynamics in wastewater systems[70]. Wolff et al. (2020)[62] documented correlations between microplastics and total suspended solids. Their examination of two municipal WWTPs revealed approximately 0.28 particles/mg total suspended solids in Mannheim and 0.23 particles/mg total suspended solids in Frankfurt-Sindlingen[62]. A comparative analysis of six WWTPs in Thailand revealed significant positive correlations between microplastics abundance, total suspended solids, and turbidity, with suspended solids identified as the most reliable predictor of microplastic concentrations (adjusted R^2 = 0.91, p = 0.001)[60]. Fine particles predominated in the influent microplastic fractions. Particles in the 100-300 μm size range were predominant in influent samples, with removal efficiencies across various treatment processes reported between 86.0% and 98.5%[60]. These findings underscore the importance of routine monitoring. Thus, routinely assessed parameters like turbidity and total suspended solids may serve as practical and cost-effective indicators for monitoring microplastic concentrations in wastewater treatment systems[60]. Progress in sensing technologies enables real-time monitoring. Innovative optical sensors integrating microscopic imaging with automated classification algorithms are being developed to differentiate microplastic particles from natural substances like sand or organic matter in continuous water flows. García-Valle et al. (2025)[71] presented an optical monitoring methodology. Their research introduced a prototype optical sensor capable of detecting microplastics in seawater through automated image analysis and experimental validation in controlled settings[71]. Preliminary experiments demonstrated promising detection performance. The findings indicate that optical sensing systems could provide a feasible method for continuous environmental monitoring of microplastics in aquatic ecosystems[71].

While the technology has primarily been evaluated in marine systems, similar methodologies could be adapted for wastewater treatment facilities, where influent streams constitute a major pathway for microplastics derived from domestic wastewater, textile laundering, and industrial effluents. Optical monitoring systems may offer continuous measurements. These systems may enable automated particle classification and near-real-time characterization of microplastic concentrations entering wastewater treatment facilities via influent streams. When integrated with operational parameters such as flow rate, turbidity, and total suspended solids, these monitoring methodologies could support the establishment of early warning systems capable of detecting anomalous microplastics surges and improving the understanding of pollution sources within sewer systems. Such approaches may strengthen monitoring strategies. They may also support improved management of microplastics contamination within wastewater treatment systems. Although these developments highlight considerable potential for improving monitoring, the operational perspective of WWTP management remains insufficiently addressed. From the viewpoint of plant operators, the practical integration of AI-based monitoring systems within existing operational infrastructures requires further attention. In particular, the connection between anomaly detection and concrete operational responses, such as adjustments to primary treatment processes, sludge recirculation, or influent flow management, has not yet been sufficiently explored. Furthermore, the effective incorporation of AI-driven monitoring tools into existing supervisory control and data acquisition (SCADA) systems and routine plant instrumentation is essential for real-world implementation. Operational conditions that influence influent characteristics, including stormwater inflow, combined sewer overflows, and daily variability in wastewater composition, should also be more explicitly considered when developing predictive monitoring frameworks. Addressing these operational aspects would significantly strengthen the practical applicability of AI-assisted monitoring systems and enhance their value for real-time decision-making in WWTPs.

Evidence from microplastics monitoring studies in WWTPs (2019–2026)

Research in aquatic and wastewater systems between 2019 and 2026 is listed in Table 4. The studies illustrate how ML techniques are increasingly used to support tasks such as particle identification, source apportionment in WWTPs, prediction of treatment performance, and analysis of microplastics impacts on biological processes. Several studies focus on automated identification of microplastics from imaging or spectroscopic data. For example, Convolutional Neural Networks applied to microscopic images of cosmetic microbeads achieved classification accuracies of approximately 97% in pure water samples and 89% in wastewater conditions. Similarly, deep learning

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models applied to FT-IR spectra reported true positive rates close to 0.99–1.00 for polymer recognition, while also reducing analysis time compared with conventional spectral library searches. Other studies demonstrate the use of ML for process modeling and environmental interpretation. In full-scale WWTP investigations, decision tree, random forest, and support vector machine models achieved prediction accuracies between 88.9% and 92.3% when identifying the main sources of microplastics entering treatment systems. Predictive modeling approaches have also been used to estimate removal efficiency during coagulation processes, with reported model performance reaching R^2 values up to 0.98.

Although these results highlight the potential of AI for improving microplastics monitoring and data interpretation, several studies also emphasize important limitations. Many models rely on relatively small datasets or on narrowly defined polymer categories, which may restrict their transferability to other treatment plants or environmental conditions. Overall, the studies summarized in Table 4 demonstrate that AI techniques can significantly improve automated detection, predictive modeling and data analysis of microplastics in wastewater systems, but further work is needed to expand datasets and improve model generalization.

Potential operational impacts of AI systems in WWTPs

Table 5 provides an overview of the principal operational domains in which AI can support WWTP performance in relation to microplastics management. It summarizes current applications of data-driven approaches across monitoring, prediction, and process control. A closer examination, however, indicates that the level of development of these applications is not uniform. Several studies report promising results, especially in influent characterization, surrogate-based estimation of microplastics loads, and process optimization. Yet the available evidence remains fragmented. Reported model performance often depends on site-specific datasets, which limits both comparison across studies and transferability between treatment plants. In addition, important gaps remain. Direct links between operational parameters and measured microplastic concentrations are still limited, since most approaches rely on indirect indicators such as turbidity and total suspended solids. This dependence introduces considerable uncertainty in assessing treatment performance. Evidence for stable full-scale implementation is also scarce, particularly for AI-driven control under dynamic operating conditions. Some studies demonstrate strong performance. Others highlight clear constraints. This variability reflects the absence of standardized datasets and benchmarking approaches. Overall, AI shows clear potential, but most applications remain at an early stage. Further progress will require improved monitoring infrastructure, long-term datasets, closer integration with SCADA systems, and the development of practical and scalable implementation pathways.

AI is increasingly being discussed not only as a monitoring tool, but also as a possible support mechanism for operational management in WWTPs. Beyond particle detection and classification, several recent studies have explored whether AI-based systems could assist operators in responding more effectively to changes in treatment performance and microplastics behavior within WWTPs. In this context, predictive models may provide early indications of increased microplastic concentrations, abnormal particle distributions, or process instability during plant operation.

For example, elevated microplastics loads detected in influent streams could indicate the need for operational adjustments during coagulation and flocculation processes in order to improve particle aggregation and retention. Similarly, AI-assisted monitoring of membrane systems may help identify declining filtration performance or conditions associated with membrane fouling before severe operational deterioration occurs. Operational parameters such as sludge recirculation rate, suspended solids concentration, and sludge-retention time may also be evaluated together with microplastics monitoring data to better understand particle transport within activated sludge systems and support process optimization. At the same time, the practical implementation of these approaches remains relatively limited. Most currently available studies are still based on laboratory-scale experiments, pilot systems, or controlled datasets rather than full-scale operational environments. Consequently, although AI-assisted monitoring and forecasting systems appear promising for intelligent wastewater management, additional validation under real operating conditions is still required before these approaches can be routinely integrated into WWTP operational practice.

Potential economic and operational benefits of AI in WWTPs

AI has increasingly been examined in wastewater treatment research because modern WWTPs are associated with high operational complexity and significant energy demand. Several studies have investigated the application of AI-based approaches for process optimization, operational control, and predictive maintenance within wastewater systems. By analyzing large operational datasets, AI models may identify interactions between operational variables that are difficult to detect through conventional mechanistic approaches. Process optimization is among the most widely investigated applications. Predictive maintenance has also attracted considerable attention in recent years. AI-assisted systems may support early detection of operational abnormalities before severe equipment malfunction occurs, potentially reducing downtime and improving operational stability within treatment facilities[75]. Economic benefits associated with AI-assisted wastewater management have also been reported. Hybrid computational models combining optimization and prediction techniques demonstrated predictive accuracies ranging from 0.64 to 1.00, while operational cost reductions approaching 30% were observed in several investigations[18].

Energy optimization remains one of the principal fields of AI application in WWTPs. An adaptive kernel-function model combined with a multi-objective optimal control strategy achieved measurable reductions in energy demand during stormy, rainy and dry-weather operating conditions compared with conventional control approaches[76]. Aeration control has received particular attention because aeration generally represents one of the most energy-intensive stages of wastewater treatment operation. At a wastewater treatment facility in Detroit, the implementation of a data-mining model reduced energy consumption by approximately 31.4% while maintaining effluent quality within regulatory standards[77]. Comparable findings were reported in studies combining statistical-learning techniques with deep reinforcement learning, where electricity savings close to 16.7% were achieved relative to conventional operating strategies[78]. AI-based optimization methods have also been evaluated in sewage pumping systems. Neural-network models improved pump scheduling and operational control, resulting in average energy savings of approximately 10%, whereas reductions approaching 25% were reported under favorable operating conditions[79]. Hierarchical systems combining model predictive control with feedforward control demonstrated smaller but still meaningful reductions in operating costs and aeration-energy demand[80]. AI applications have additionally been proposed during the planning and design stages of wastewater treatment

Table 4 AI applications for microplastics detection, monitoring, and modeling in aquatic and wastewater systems (2019–2026).

Reference	Study environment	Dataset / analytical method	AI technique	Target application	Model performance	Key contribution	Limitation
[72]	Urban water and wastewater; microscope-based analysis of cosmetic microbeads	42,928 microscopic images of microbeads from 5 cleanser products; images obtained under water/wastewater conditions and with different filters/slides	Convolutional Neural Networks (GoogLeNet)	Classification of microbeads and identification of the product origin from microscopic images	97% accuracy in pure water and 89% in wastewater	First reported use of neural network for microplastics classification; showed Convolutional Neural Networks can classify microbeads accurately under varying imaging conditions	Restricted to microbeads from 5 cosmetic products and image-based classification rather than broader polymer identification
[67]	WWTO-derived environmental sample analyzed by FPA-based micro-FT-IR	FT-IR spectra converted to 2-D spectrograms; 415 PP spectra, 256 PE spectra and 921 background spectra; 50/50 train-test split	Deep Convolutional Neural Networks (VGG-based PlasticNet)	Automatic microplastics recognition via FT-IR spectroscopy	True positive rates: 1.00 for PP, 0.99 for background, 0.99 for PE; 46% faster than library search (62 vs 114 min)	Demonstrated that deep learning can outperform conventional library-search FT-IR analysis and recover PP particles missed by library search	Requires large spectral corpora (minimum 200 spectra per type for optimal results); future work needed to expand polymer variety and training spectra; PE/acrylate similarity remained an issue
[73]	Anaerobic digestion of waste activated sludge in wastewater treatment context	Literature-derived dataset from 5 studies; 871 data points; inputs included digestion time, microplastics type, diameter, concentration, substrate type and substrate concentration	AutoML frameworks (TPOT, GAMA, AutoGluon, H2o AutoML); best-performing models were GBM-based	Prediction of microplastics-induced effects on methane production and explainable modeling of key drivers	GBM achieved MSE = 17.0 versus 58.0 for common neural network models; GAMA reached MSE = 12.8 and AutoGluon selected CatBoost with MSE = 17.0	Showed that AutoML can identify optimized predictive models without manual intervention; microplastics type was more influential than size and concentration and polystyrene was associated with higher methane production	Dataset size was limited because only studies reporting all selected variable could be used; authors also noted the need for better characterization of microplastics in anaerobic digestion
[51]	Four full-scale WWTPs in Hong Kong (wastewater and sludge across treatment units)	Full-scale field investigation with MP physicochemical characterization, PCA and source tracing from environmental samples	Multilabel decision tree, Random Forest, support vector machines	Source apportionment and interpretation of fate of MPs in WWTPs	Accuracy: 88.9% (decision tree), 91.4% (RF), 92.3% (support vector machine)	Demonstrated that domestic sources dominated MPs in Hong Kong WWTPs (57.3–59.9%), followed by industrial sources (21.1–21.7%); linked source composition to WWTP design and MP physicochemical traits	Study scope was limited to four Hong Kong WWTPs, so transferability to other regions and sewerage configurations should be interpreted cautiously
[52]	Water and wastewater treatment during coagulation processes	Experimental coagulation datasets using operating variables such as MP minimum/maximum size, coagulant dose, pH, temperature and coagulant aid	ANN, PSO-ANFIS, LSSVM,RBF	Prediction of microplastics removal efficiency during coagulation	R^2 = 0.91 (ANN), 0.88 (PSO-ANFIS), 0,85 (LSSVM), 0.8 (RBF)	Showed that RBF provided the best predictive accuracy; sensitivity analysis identified water temperature as the strongest negative factor and coagulant-aid type/dose as the most positive factors for MP removal	Focused specifically on coagulant and selected operational variables, so the framework does not represent all MP removal mechanism across treatment trains
[74]	Constructed wetlands treating nitrogen-containing wastewater; CWs as MP sinks	Meta-analysis of 1903 datasets from 34 studies; RF model with SHAP; variables included MP characteristic, dosage frequency, exposure duration and CW operational parameters	Random Forest regression with SHAP interpretation	Prediction and interpretation of MPs effects on nitrogen removal performance in constructed wetlands	TN model: R^2 train = 0.981, R^2 train = 0.95, RMSE = 3.2423; NH_4^+–N model: R^2 train = 0.882, R^2 train = 0.793, RMSE = 5.7866; NO_3^-–N model: R^2 train = 0.794, R^2 train = 0.702, RMSE = 6.8583	Combined meta-analysis with interpretable ML to show that dosage frequency and exposure duration were the dominant activity, enzymes, genes and plant stress responses	Prediction for NH_4^+–N and NO_3^-–N remained less accurate because of limited microbial data and complex, partly unquantifiable nitrogen-cycle regulation

facilities. Decision-support frameworks integrating ANNs, genetic algorithms, fuzzy logic and expert systems were used to compare alternative operational and design scenarios. According to these investigations, treatment costs could potentially decrease during both plant construction and long-term operation[81]. Industrial applications further demonstrate the economic value of AI-assisted wastewater management systems. In one industrial case study, a real-time monitoring platform connected to IoT sensors reduced trade-waste fees by approximately 26%, corresponding to annual savings close to €211,500[82]. Similar improvements were reported in Germany, where aeration optimization at a wastewater treatment facility in Cuxhaven achieved approximately 30% lower aeration-energy consumption, corresponding to annual savings of around 1.1 million kWh[83]. More recent investigations also examined hybrid AI-control systems under full-scale operating conditions. An LSTM-Fuzzy Inference aeration-control model maintained dissolved oxygen concentrations within ±0.5 mg/L of the target set point for 53 consecutive days while substantially reducing dissolved oxygen overshoot events. During the same operational period, operational expenditure (OPEX) decreased by approximately €165,600 over six months[84]. Overall, recent studies indicate that AI-assisted approaches may support more adaptive and energy-efficient wastewater treatment operation. Compared with conventional mechanistic control strategies, AI-based systems are capable of capturing nonlinear relationships between operational variables and treatment performance. Consequently, such approaches are increasingly considered promising tools for improving the operational and economic sustainability of WWTPs[85].

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Table 5 Potential operational impacts of AI implementation for microplastics management in WWTPs.

Operational domain	AI-driven analytical approach	Key operational variable	Technical application in WWTP operation	Expected operational benefit	Limitations	Technology maturity level	Reference
Influent microplastics characterization	ML models for anomaly detection and pattern recognition	Flow rate, turbidity, total suspended solids, particle load	Early detection of abnormal influent particle loads potentially associated with microplastics inputs	Improved operational preparedness and stabilization of treatment performance under variable microplastics loads	Accuracy depends on the availability and quality of continuous monitoring data and reliable sensor calibration	Medium (pilot-scale applications, limited full-scale validation)	[18, 62]
Microplastics load estimation	Data-driven regression models using surrogate monitoring indicators	Total suspended solids, turbidity, particle size distribution	Estimation of microplastic concentrations using routinely monitored operational parameters	Reduced analytical costs and improved temporal resolution of microplastics monitoring	Indirect estimation introduces significant uncertainty due to weak relationships with actual microplastic concentrations	Low (early-stage, limited validation datasets)	[51, 54]
Microplastics accumulation in sludge	Predictive modeling of particle partitioning within treatment processes	Sludge retention time (SRT), MLSS, sludge recirculation ratio	Prediction of microplastics accumulation and distribution within sludge streams	Improved sludge management strategies and reduced environmental transfer through sludge reuse	Limited availability of validated datasets linking operational parameters with microplastics partitioning	Low (conceptual and modeling stage)	[51, 54]
Biological reactor performance	AI-assisted process control and predictive modeling	Dissolved oxygen (DO), hydraulic retention time (HRT), biomass concentration	Optimization of aeration intensity and biological reactor conditions affecting particle retention	Improved removal efficiency of suspended particles and enhanced microplastics capture within sludge flocs	Implementation may require advanced control infrastructure and integration with plant SCADA systems	Medium to high (applied in process control, limited microplastics-specific validation)	[36, 66]
Operational anomaly detection	Deep learning models for fault detection in treatment processes	Sensor datasets, turbidity fluctuations, flow variability	Detection of abnormal plant behavior that may influence particle transport and microplastics release	Early operational intervention and improved system resilience	Model performance may decline when operational conditions differ from training datasets	Medium (established in WWTP monitoring, limited microplastics focus)	[18, 39]
Energy optimization in microplastics removal processes	AI-based predictive control of aeration and pumping systems	Oxygen demand, airflow rate, plant energy consumption	Optimization of aeration and hydraulic conditions indirectly influencing microplastics retention	Reduced energy consumption and improved operational cost efficiency	Requires reliable energy monitoring infrastructure and consistent process data availability	High (well-established in WWTPs, indirect relevance to microplastics)	[66, 68]

Challenges and future directions of AI-assisted approaches

The use of AI in the monitoring of microplastics in WWTPs has received increasing attention during the last few years. Even so, its application in real wastewater systems is still accompanied by several practical and methodological limitations. One of the most persistent problems is related to the availability of suitable datasets. In many studies, the data used for model development originate from relatively small monitoring campaigns and laboratory analyses. Because of this, predictive models often perform well within the original dataset but show limited reliability when applied to different treatment plants or operational conditions[51, 54]. Another difficulty stems from the absence of standardized monitoring approaches in microplastics research. Sampling procedures, particle size thresholds, digestion methods, imaging conditions, and analytical identification techniques can vary significantly between studies. As a result, datasets generated in different investigations are not always directly comparable. Microplastics monitoring typically involves several sequential steps, including sample preparation, filtration, and spectroscopic identification of polymers. Each of these steps may influence the number and characteristics of the particles that are finally reported[47, 48]. For this reason, many researchers emphasize that more consistent monitoring protocols would greatly improve the reliability and comparability of microplastics datasets. Another major constraint to wider adoption of AI in microplastics monitoring is the quality of the available datasets. Many existing studies are based on relatively short monitoring periods or limited numbers of samples, which limits the ability to capture the variability normally encountered in full-scale WWTP operation. Seasonal effects, influent composition variability, and operating conditions variation over time might influence microplastics occurrence and treatment performance. This introduces further uncertainties in the model development and validation. Progress in this area will therefore depend not only on larger datasets but also on adopting more consistent monitoring practices, including comparable sampling strategies, clearer particle-size criteria, and more harmonized sample preparation procedures across studies. The behavior of microplastics inside WWTPs adds an additional layer of complexity. Particle transport and retention depend on several interacting factors such as particle size, morphology, polymer density, influent composition, hydraulic conditions, and the configuration of the treatment process itself[51, 54, 58]. These factors rarely act independently. Instead, they interact with one another and often create nonlinear system dynamics. Although machine-learning algorithms are capable of capturing such complex relationships, their predictive performance still depends heavily on the quality and representativeness of the available data[51, 54]. For this reason, many existing studies concentrate mainly on automated particle identification or classification rather than on predicting the full behavior of microplastics throughout the treatment process. The limited portability of AI models across WWTPs

remains a key obstacle to their practical use. A model calibrated with data from one facility may not respond in the same way when influent composition, hydraulic behavior, treatment layout, or monitoring frequency changes. This is particularly important for microplastics, where the available datasets are often small, irregular, and strongly affected by local conditions. Future work should therefore move beyond single-site model development and examine strategies that allow knowledge to be transferred between facilities. Transfer learning is relevant in this context, as information gained from data-rich plants could be used to support model development in WWTPs with shorter monitoring records. Federated learning may also be useful, particularly when several facilities can contribute to model training without exchanging raw operational data. These directions would help make AI-based microplastics monitoring less dependent on isolated datasets and more suitable for wider implementation in real treatment systems. Practical implementation in WWTPs presents additional challenges. Most facilities rely on established SCADA systems together with sensor networks that continuously monitor parameters such as flow rate, turbidity, dissolved oxygen, and total suspended solids. Some of these routinely measured parameters may show relationships with microplastic concentrations. For instance, turbidity and suspended solids have been proposed as possible proxy indicators that could help estimate microplastics abundance in wastewater streams. However, these relationships are still at a very early stage and have not yet been sufficiently validated across different treatment plants and operational conditions. A further challenge concerns the connection between analytical monitoring and plant operation. Even when AI models identify unusual patterns in monitoring data, it is not always clear how this information should translate into operational responses. In practice, such responses might involve adjustments to primary clarification processes, changes in sludge recirculation strategies, or modifications in influent flow management[71]. Without this operational link, AI systems risk remaining analytical tools rather than becoming practical decision-support instruments for plant operators. Despite these limitations, the outlook for AI-supported monitoring remains encouraging. Rapid developments in sensing technologies, automated image analysis, and high-frequency environmental monitoring are expected to generate larger and more consistent datasets suitable for machine-learning applications. Optical sensing technologies that combine microscopic imaging with automated particle classification already demonstrate the capability to detect microplastics particles in flowing water[71]. Such systems could eventually enable near-real-time monitoring of microplastics in WWTPs. However, the practical deployment of such systems in full-scale WWTPs remains challenging because real-time image analysis and deep learning applications often require substantial computational resources and edge-computing infrastructure. High-performance models such as Convolutional Neural Networks may depend on local GPUs or dedicated processing units in order to support continuous data acquisition and real-time prediction. As a result, future implementation strategies will need to balance model complexity and predictive accuracy with the computational, economic, and operational constraints of on-site deployment. Lightweight AI architectures and optimized edge-computing approaches may therefore become increasingly important for the development of reliable early warning systems in wastewater treatment applications. Future research will therefore need to focus on improving both data quality and operational integration. The development of standardized monitoring methodologies would increase dataset comparability and support the construction of more reliable predictive models. At the same time, closer collaboration between environmental scientists, wastewater engineers, and data scientists will be necessary in order to link particle-level observations with plant-scale operational data. If these challenges are addressed, AI may gradually transform microplastics monitoring from a primarily laboratory-based activity into a predictive management tool capable of supporting more effective control of microplastics emissions from WWTPs.

Future research should also pay greater attention to the development of open-access datasets for microplastics monitoring in WWTPs. At present, many of the datasets available in the literature are relatively small and often produced using different monitoring strategies and analytical procedures. As a result, direct comparisons between studies are not always straightforward, and model validation across different treatment plants remains limited. More standardized and publicly accessible datasets could therefore support the development of AI models that are more reliable under a wider range of operational conditions. Another important issue concerns the interpretability of AI-assisted monitoring systems. Although many machine learning models can provide strong predictive performance, the way these models generate predictions is often difficult to understand during practical plant operation. For this reason, explainable AI approaches may become increasingly important in future wastewater applications. Improving model transparency could help operators better understand how AI predictions relate to treatment efficiency, process behavior, and operational decision-making within WWTPs. The economic feasibility of AI implementation should also be examined more carefully in future studies. The infrastructure requirements, computational demand, and maintenance costs associated with AI-assisted monitoring systems may differ considerably between small and large wastewater treatment facilities. Consequently, techno-economic assessments and cost–benefit analyses will likely become necessary before AI-assisted systems can be more broadly integrated into full-scale wastewater treatment practice.

Conclusions

Microplastics are increasingly recognized as a widespread form of pollution in aquatic environments and have been reported in rivers, lakes, coastal areas, and even remote ecosystems. Because WWTPs collect wastewater from domestic, industrial, and urban sources before discharge, they represent an important control point for limiting the release of microplastics into natural waters. However, conventional treatment systems were originally designed to remove organic matter, nutrients, and suspended solids rather than extremely small particles such as microplastics. Influent concentrations reported in the literature range from approximately 0.4 particles/L to more than 7,216 particles/L, while effluent concentrations typically vary between 0.05 and 994 particles/L depending on treatment configuration and analytical techniques. Although removal efficiencies can appear relatively high, the large volumes of treated wastewater mean that a substantial number of particles may still be released into receiving waters. The behavior of microplastics within treatment systems is influenced by particle size, shape, and density. Smaller particles tend to remain suspended and are more difficult to remove. Removal occurs progressively, with preliminary and primary stages removing around 72% of particles, secondary treatment increasing removal to approximately 88%, and tertiary processes reaching up to 94%. However, particles smaller than about 150 μm can pass through treatment systems. A significant fraction (60–80%) of retained microplastics accumulates in sewage sludge, creating an additional pathway for environmental contamination when sludge is applied to agriculture, where concentrations can reach approximately 3500 particles/kg. These findings suggest that wastewater treatment may

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partially shift microplastics contamination from aquatic systems to land environments. Accurate monitoring of microplastics in WWTPs remains essential. Analytical techniques can provide valuable information on particle characteristics, but they are often time-consuming and contribute to inconsistencies due to differences in sampling and methodology. This highlights the need for more standardized monitoring approaches. In recent years, AI and ML approaches have begun to play a role in microplastics research. These tools can assist in particle identification and classification, with reported accuracies exceeding 95% in some cases. ML models can also be applied to operational data to examine treatment performance and support predictive monitoring. In addition, AI-based optimization has been associated with energy savings ranging from approximately 10% to over 30%. Overall, WWTPs play a key role in reducing microplastics discharge, although complete removal remains challenging. Future efforts should focus on improving monitoring methods, increasing methodological consistency, and integrating data-driven approaches such as AI to support more efficient and sustainable management of microplastics.

Ethical statements

Not applicable.

Author contributions

Konstantinos Tsamoutsoglou conceived the study, designed the structure of the review, and wrote the original draft. Vasileia Gkika contributed to literature collection, data analysis, and manuscript editing. Li Xu contributed to conceptual development, critical revision of the manuscript, and supervision. All authors reviewed and approved the final version of the manuscript.

Data availability

No new datasets were generated or analyzed in this study. All data supporting the findings are derived from previously published literature and are available from the corresponding references cited in the manuscript.

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Competing interests

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References

[1] Bashir MJK, Mojiri A. 2022. Recent developments in emerging contaminants determination and treatment technologies. *Separations* 9:434

[2] Meaza I, Toyoda JH, Wise Sr JP. 2021. Microplastics in sea turtles, marine mammals and humans: A one environmental health perspective. *Frontiers in Environmental Science* 8:575614

[3] Bai S, Wang L, Ma F, Zhu S, Xiao T, et al. 2020. Self-assembly biochar colloids mycelial pellet for heavy metal removal from aqueous solution. *Chemosphere* 242:125182

[4] Dris R, Gasperi J, Mirande C, Mandin C, Guerrouache M, et al. 2017. A first overview of textile fibers in indoor and outdoor environments. *Environmental Pollution* 221:453–458

[5] Van Sebille E, Wilcox C, Lebreton L, Maximenko N, Hardesty BD, et al. 2015. A global inventory of small floating plastic debris. *Environmental Research Letters* 10:124006

[6] Karlsson TM, Vethaak AD, Almroth BC, Ariese F, van Velzen M, et al. 2017. Screening for microplastics in sediment, water, marine invertebrates and fish: Method development and microplastic accumulation. *Marine Pollution Bulletin* 122:403–408

[7] Bläsing M, Amelung W. 2018. Plastics in soil: Analytical methods and possible sources. *Science of the Total Environment* 612:422–435

[8] Van Cauwenberghe L, Janssen CR. 2014. Microplastics in bivalves cultured for human consumption. *Environmental Pollution* 193:65–70

[9] Barboza LGA, Gimenez BCG. 2015. Microplastics in the marine environment: Current trends and future perspectives. *Marine Pollution Bulletin* 97:5–12

[10] Yaqoob AA, Parveen T, Umar K, Ibrahim MNM. 2020. Role of nanomaterials in the treatment of wastewater: A Review. *Water* 12:495

[11] Ekener E, Hansson J, Larsson A, Peck P. 2018. Developing life cycle sustainability assessment methodology by applying values-based sustainability weighting - tested on biomass based and fossil transportation fuels. *Journal of Cleaner Production* 181:337–351

[12] Cairone S, Hasan SW, Choo KH, Lekkas DF, Fortunato L, et al. 2024. Revolutionizing wastewater treatment toward circular economy and carbon neutrality goals. *Journal of Water Process Engineering* 63:105486

[13] Shiraki A, Sakimoto S, Tsuboi K, Wakabayashi T, Hara C, et al. 2019. Evaluation of retinal nonperfusion in branch retinal vein occlusion using wide - field optical coherence tomography angiography. *Acta Ophthalmologica* 97:e913–e918

[14] Yin H, Xu M, Luo Z, Bi X, Li J, et al. 2024. Machine learning for membrane design and discovery. *Green Energy and Environment* 9:54–70

[15] Alam G, Ihsanullah I, Naushad M, Sillanpää M. 2022. Applications of artificial intelligence in water treatment for optimization and automation of adsorption processes: Recent advances and prospects. *Journal of Water Process Engineering* 427:130011

[16] Nguyen XC, Nguyen TTH, La DD, Kumar G, Rene ER, et al. 2021. Development of machine learning-based models to forecast solid waste generation in residential areas: A case study rom vietnam. *Resources, Conservation and Recycling* 167:105381

[17] Ye Z, Yang J, Zhong N, Tu X, Jia J, et al. 2020. Tackling environmental challenges in pollution controls using artificial intelligence: A review. *Science of the Total Environment* 699:134279

[18] Zhao L, Dai T, Qiao Z, Sun P, Hao J, et al. 2020. Application of artificial intelligence to wastewater treatment: A bibliometric analysis and systematic review of technology, economy, management, and wastewater reuse. *Process Safety and Environmental Protection* 133:169–182

[19] Wen CH, Vassiliadis CA. 1998. Applying hybrid artificial intelligence techniques in wastewater treatment. *Engineering Applications of Artificial Intelligence* 11:685–705

[20] Sharafati A, Asadollah SBHS, Hosseinzadeh M. 2020. The potential of new ensemble machine learning models for effluent quality parameters prediction and related uncertainty. *Process Safety and Environmental Protection* 140:68–78

[21] Niu G, Yi X, Chen C, Li X, Han D, et al. 2020. A novel effluent quality predicting model based on genetic-Deep belief network algorithm for cleaner production in a full-scale paper-making wastewater treatment. *Journal of Cleaner Production* 265:121787

[22] Xin C, Shi X, Wang D, Yang C, Li Q, et al. 2020. Multi-grained cascade forest for effluent quality prediction of papermaking wastewater treatment processes. *Water Science and Technology* 81:1090–1098

[23] Newhart KB, Marks CA, Rauch-Williams T, Cath TY, Hering AS. 2020. Hybrid statistical-machine learning ammonia forecasting in continuous activated sludge treatment for improved process control. *Journal of Water Process Engineering* 37:101389

[24] Mei R, Kim J, Wilson FP, Bocher BTW, Liu W. 2019. Coupling growth kinetics modeling with machine learning reveals microbial immigration impacts and identifies key environmental parameters in a biological wastewater treatment process. *Microbiome* 7:65

[25] Nourani V, Elkiran G, Abba SI. 2018. Wastewater treatment plant performance analysis using artificial intelligence—An ensemble approach. *Water Science and Technology* 78:2064–2076

[26] Picos-Benítez AR, López-Hincapié JD, Chávez-Ramírez AU, Rodríguez-García A. 2017. Artificial intelligence based model for optimization of COD removal efficiency of an up-flow anaerobic sludge blanket reactor in the saline wastewater treatment. *Water Science and Technology* 75:1351–1361

[27] Kern P, Wolf C, Gaida D, Bongards M, McLoone S. 2014. COD and NH_4-N estimation in wastewater treatment inflow using machine learning techniques. *IEEE Conference on Automation Science and Engineering*. pp. 812-817 https://doi.org/10.1109/CoASE.2014.6899419

[28] Yoo C, Hwang S, Moon I. 2008. Hybrid fuzzy modeling of wastewater quality with Artificial Intelligence learning. *Environmental Engineering Science* 25:941–950

[29] Wang Z, Man Y, Hu Y, Li J, Hong M, et al. 2019. A deep learning-based dynamic COD prediction model for urban sewage. *Environmental Science: Water Research and Technology* 5:2210–2218

[30] Oulebsir R, Lefkir A, Safri A, Bermad A. 2020. Optimization of the energy consumption in activated sludge process using deep learning selective modeling. *Biomass and Bioenergy* 132:105420

[31] Mercier T, Dembélé A, Denœux T, Blanc P. 2019. Machine learning as a decision support tool for wastewater treatment plant operation. *Water Resources Management X* 3:103–107

[32] Liu Y, Guo J, Wang Q, Huang D. 2016. Prediction of filamentous sludge bulking using gaussian processes regression model. *Scientific Reports* 6:31303

[33] De Cañete JF, del Saz-Orozco P, Gómez-de-Gabriel J, Baratti R, Ruano A, et al I. 2021. Control and soft sensing strategies for a wastewater treatment plant using neuro-genetic approach. *Computers and Chemical Engineering* 144:107146

[34] Osman YBM, Li W. 2020. Soft sensor modeling of key effluent parameters in wastewater treatment process based on SAE-NN. *Journal of Control Science and Engineering* 2020:6347625

[35] Yan W, Xu R, Wang K, Di T, Jiang Z. 2020. Soft sensor modeling based on semisupervised deep learning and its application to wastewater treatment plant. *Industrial and Engineering Chemistry Research* 59:4589–4601

[36] Cheng T, Harrou F, Kadri F, Sun Y, Leiknes T. 2020. Forecasting wastewater treatment plant key features using deep learning-based models: A case study. *IEEE Access* 8:184475–184485

[37] Hernández-del-Olmo F, Gaudioso E, Duro N, Dormido R. 2019. Machine learning soft-sensor for advanced control of wastewater treatment plants. *Sensors* 19:3139

[38] Zhuang Z, Sun Z, Cheng Y, Yao R, Zhang W. 2018. Modeling and optimization of paper-making wastewater treatment using reinforcement learning. *Chinese Control Conference*. pp. 8342–8346 https://doi.org/10.23919/ChiCC.2018.8482733

[39] Mamandipoor B, Majd M, Sheikhalishahi S, Modena C, Osmani V. 2020. Monitoring and detecting faults in wastewater treatment plants using deep learning. *Environmental Monitoring and Assessment* 192: 148 https://link.springer.com/article/10.1007/s10661-020-8064-1

[40] Dairi A, Cheng T, Harrou F, Sun Y, Leiknes T. 2019. Deep learning approach for sustainable WWTP Operation: A case study on data-driven influent conditions monitoring. *Sustainable Cities and Society* 50:101670

[41] Harrou F, Dairi A, Sun Y, Senouci M. 2018. Wastewater treatment plant monitoring via deep learning. *In: IEEE International Conference on Industrial Technology*. pp. 1544–1548 https://doi.org/10.1109/ICIT.2018.8352410

[42] Torregrossa D, Leopold U, Hernández-Sancho F, Hansen J. 2018. Machine learning for energy cost modeling in wastewater treatment plants. *Journal of Environmental Management* 223:1061–1067

[43] Iyare PU, Ouki SK, Bond T. 2020. Microplastics removal in wastewater treatment plants: A critical review. *Environmental Science: Water Research and Technology* 6:2664–2675

[44] Mabadahanye K, Dalu MTB, Dalu T. 2024. Occurrence and removal of microplastics in wastewater treatment plants: perspectives on shape, type, and density. *Water* 16:1750

[45] Miserli K, Konstantinou I. 2025. Determination of microplastics in municipal wastewater treatment plant effluents and sludge using micro-Raman spectroscopy. *Water Emerging Contaminants and Nanoplastics* 4:1

[46] Amparán MAA, Palacios A, Flores GM, Olivera PMC. 2025. Review and future outlook for the removal of microplastics by physical, biological and chemical methods in water bodies and wastewaters. *Environmental Monitoring and Assessment* 197:429

[47] Bodzek M, Pohl A, Rosik-Dulewska C. 2024. Microplastics in wastewater treatment plants: Characteristics, occurrence and removal technologies. *Water* 16:3574

[48] Periyasamy AP, Perumalsamy R. 2025. Machine learning for microplastics quantification: Techniques, challenges, and future directions. *Cleaner Water* 100158 https://doi.org/10.1016/j.clwat.2025.100158

[49] Felsing S, Kochleus C, Buchinger S, Brennholt N, Stock F, et al. 2018. A new approach in separating microplastics from environmental samples based on their electrostatic behavior. *Environmental Pollution* 234:20–28

[50] Karapanagioti HK, Kalavrouziotis IK. 2019. Microplastics in water and wastewater. Iwa Publishing https://doi.org/10.2166/9781789060034

[51] Wu P, Wang B, Lu Y, Cao G, Xie P, et al. 2024. Machine learning-assisted insights into sources and fate of microplastics in wastewater treatment plants. *ACS ES& T Water* 4:1107–1118

[52] Hosseinzadeh A, Amirkhani F, Azizi N, Dashti A, Zhou J, et al. 2025. Machine learning modeling of microplastics removal by coagulation in water and wastewater treatment. *Journal of Water Process Engineering* 76:108108

[53] Liu L, Ye Q, Wu Q, Liu T, Peng S. 2021. Effect of biochar addition on sludge aerobic composting and greenbelt utilization. *Environmental Technology and Innovation* 21:101279

[54] Austin ES, Austin DM, Tseng LY, Liu L, Kleinmeyer Z, et al. 2025. Meta-analysis on microplastics monitoring in global water resource recovery facilities: An emphasis on overlooked factors. *Environmental Pollution* 386:127220

[55] Zhu Y, Yang S, Gustavsson M, Huang W, Gao S, et al. 2025. Investigation of removal efficiency of microplastics at different process stages of a wastewater treatment plant in the textile industry in southern China. *Water* 17:574

[56] Liu W, Zhang J, Liu H, Guo X, Zhang X, et al. 2021. A review of the removal of microplastics in global wastewater treatment plants: Characteristics and mechanisms. *Environment International* 146:106277

[57] Puteri MN, Gew LT, Ong HC, Ming LC. 2025. Technologies to eliminate microplastics from water: current approaches and future prospects. *Environment International* 199:109397 https://doi.org/10.1016/j.envint.2025.109397

[58] Turan NB, Erkan HS, Engin GO. 2021. Microplastics in wastewater treatment plants: Occurrence, fate and identification. *Process Safety and Environmental Protection* 146:77–84

[59] Carnevale Miino M, Galafassi S, Zullo R, Torretta V, Rada EC. 2024. Microplastics removal in wastewater treatment plants: A review of the different approaches to limit their release in the environment. *Science of the Total Environment* 930:172675 https://doi.org/10.1016/j.scitotenv.2024.172675

[60] Huang X, Liu C, Li K, Liu F, Liao D, et al. 2013. Occurrence and distribution of veterinary antibiotics and tetracycline resistance genes in farmland soils around swine feedlots in Fujian Province, China. *Environmental Science and Pollution Research* 20:9066–9074

[61] Haq I, Shah MP. 2025. Advanced treatment technologies for the removal of microplastics in wastewater. *CRC Press* https://doi.org/10.1201/9781003379386

[62] Wolff S, Weber F, Kerpen J, Winklhofer M, Engelhart M, et al. 2020. Elimination of microplastics by downstream sand filters in wastewater treatment. *Water* 13:33

[63] Khanam MM, Uddin MK, Kazi JU. 2025. Advances in machine learning for the detection and characterization of microplastics in the environment. *Frontiers in Environmental Science* 13:1573579

[64] Theepharaksapan S, Sriromreun P, Kiattisaksiri P, Phetrak A, Molee C, et al. 2025. Occurrence of microplastics in inland and island wastewater treatment plants and the role of suspended solids as monitoring indicators. *Water* 17:3330

[65] Phengsaart T, Srichonphaisarn P, Villacorte-Tabelin M, Silwamba M, Janjaroen D, et al. 2025. Microplastics removal by flotation: Systematic review, meta-analysis, and research trends. *Water* 17:3394
[66] Liu S, Li J, Ge L, Li C, Zhao J, et al. 2021. Selective diffusive gradients in thin-films with molecularly imprinted polymer for measuring fluoroquinolone antibiotics in waters. *Science of the Total Environment* 790:148194
[67] Safeer S, Pandey RP, Rehman B, Safdar T, Ahmad I, et al. 2022. A review of artificial intelligence in water purification and wastewater treatment. *Journal of Water Process Engineering* 49:102974
[68] Zhang S, Jin Y, Chen W, Wang J, Wang Y, et al. 2023. AI in wastewater treatment: A data-driven analysis of status and trends. *Chemosphere* 336:139176
[69] Navarro JL, Castrillón-Santana M, Sánchez-Nielsen E, Zarco B, Herrera A, et al. 2021. Deep learning for automatic microplastics counting. *Science of the Total Environment* 765:142728
[70] Sun W, Gao Y, Zhou J, Shah KJ, Sun Y. 2025. An overview of the latest developments and potential paths for Artificial Intelligence in wastewater treatment systems. *Water* 17:2432
[71] Medina-Jiménez JL, Morales-Rosales LA, Arias-Lizárraga DM, Amabilis-Sosa LE, Rodriguez-Rangel H. 2025. 7-challenges with artificial intelligence and machine learning methods for implementation in water treatment and monitoring. *Applications of AI in Removal of Emerging Contaminants*. pp. 181–220 https://doi.org/10.1016/B978-0-443-26779-6.00011-5
[72] Zhou X, Li Y. 2021. Atlas of oral microbiology: From healthy microflora to disease. *Springer Nature* https://doi.org/10.1007/978-981-15-7899-1
[73] García-Valle G, Torralba-Calleja E, Ciurana FM, Campoy FJ, Ricart J, et al. 2025. Detecting microplastics in seawater with a novel optical sensor based on AI Models. *In Oceans* 2025 Brest. pp. 1–8 https://doi.org/10.1109/OCEANS58557.2025.11104700
[74] Yurtsever M, Yurtsever U. 2019. Use of a convolutional neural network for the classification of microbeads in urban wastewater. *Chemosphere* 216:271–280
[75] Xu J, Qiu T, Chen F, Zhou L, Li Y, et al. 2022. Treating mariculture wastewater using electrocoagulation-microscreen drum filter technology: Electrode passivation and influencing factors. *Environmental Engineering Science* 39:535–549
[76] Zhong N, An Q, Wen C, Yan C. 2026. Machine learning-enabled meta-analysis reveals the effect of microplastics on nitrogen removal performance in constructed wetlands and its potential mechanisms. *Environmental Research* 295:123965
[77] Dwivedi YK, Hughes L, Ismagilova E, Aarts G, Coombs C, et al. 2021. Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management* 57:101994
[78] Han H, Zhang L, Liu H, Qiao J. 2018. Multiobjective design of fuzzy neural network controller for wastewater treatment process. *Applied Soft Computing* 67:467–478
[79] Asadi A, Verma A, Yang K, Mejabi B. 2017. Wastewater treatment aeration process optimization: A data mining approach. *Journal of Environmental Management* 203:630–639
[80] Filipe J, Bessa RJ, Reis M, Alves R, Póvoa P. 2019. Data-driven predictive energy optimization in a wastewater pumping atation. *Applied Energy* 252:113423
[81] Zhang Z, Kusiak A, Zeng Y, Wei X. 2016. Modeling and optimization of a wastewater pumping system with data-Mining methods. *Applied Energy* 164:303–311
[82] Santín I, Pedret C, Vilanova R. 2015. Applying variable dissolved oxygen set point in a two level hierarchical control structure to a wastewater treatment process. *Journal of Process Control* 28:40–55
[83] Bozkurt H, van Loosdrecht MCM, Gernaey KV, Sin G. 2016. Optimal WWTP process selection for treatment of domestic wastewater: A realistic full-scale retrofitting study. *Chemical Engineering Journal* 286:447–458
[84] Susan Galer. 2021. AI start-Up gives sustainable wastewater management a high-tech refresh. *Forbes BrandVoice for SAP* https://news.sap.com/2021/12/ai-startup-gives-sustainable-wastewater-management-high-tech-refresh/
[85] Xylem Inc. 2021. Wastewater treatment plant uses AI to reduce aeration energy use by 30%. *Xylem Water Utilities News*. https://www.xylem.com/en-us/making-waves/water-utilities-news/wastewater-treatment-plant-uses-ai-to-reduce-aeration-energy-use-by-30-percent/#:~:text=Xylem%20Treatment%20System%20Optimization%20predicted%20the%20best%20set,them%20achieve%20bold%20new%20efficiencies%20and%20advance%20sustainability

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