

Editorial

The Role of Artificial Intelligence in Microplastic Pollution Studies and Management

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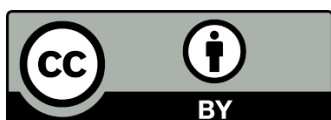
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Abstract

Artificial intelligence (AI) is reshaping microplastic research by enabling faster, more accurate, and scalable detection, characterization, and modeling. Deep learning automates the identification and classification of microplastics from microscopy images, while machine learning accelerates the recognition of polymers from Raman and infrared spectra. AI-based clustering and segmentation improve the analysis of complex samples, and source-apportionment models learn morphological and chemical features to trace emissions from various activities and land uses. AI also enhances predictions of microplastic interactions and impacts, modeling pollutant adsorption, leaching behaviors, and biological toxicity responses. Large language models are increasingly used to streamline quality assurance/control (QA/QC) and support exposure and risk assessments. Emerging AI-enabled sensors and real-time control systems can be integrated into manufacturing and wastewater treatment processes, enabling continuous monitoring and adaptive process adjustments to reduce microplastic release. Collectively, AI provides powerful tools for advancing microplastic detection, understanding their ecological and health risks, and supporting proactive pollution mitigation.

Keywords

Artificial intelligence; clustering; fate and transport; machine learning; microplastics; spectra



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1. Introduction

Microplastics, defined as plastic particles smaller than 5 mm, have become ubiquitous environmental contaminants present in aquatic ecosystems, soil, and atmospheric environments [1]. These sub-millimeter-sized plastic fragments persist in natural systems due to their resistance to degradation, accumulating across diverse environmental matrices and entering biological food chains [2, 3]. The complexity of microplastic detection stems from their small size, compositional diversity, and varying physical and chemical properties, which pose significant analytical challenges [4].

Traditional detection and quantification methods, which involve visual identification and counting under a stereomicroscope, followed by polymer identification using spectroscopy, are labor-intensive and time-consuming. These protocols require specialized expertise for accuracy and cannot reliably detect particles below 20-50 μm , while leaving nanoplastics ($<1\ \mu\text{m}$) undetectable [5]. Recent advances in microplastic identification have focused on improving sensitivity, accuracy, and throughput across various analytical platforms. Automated spectroscopic imaging techniques such as micro-Fourier Transform Infrared Spectrometry (μFTIR) and μRaman mapping now allow high-resolution, chemical-specific identification of particles down to the low-micrometer scale [4]. Advanced microscopy and 3D imaging methods, including scanning electron microscopy, atomic force microscopy, and confocal microscopy, provide detailed morphological characterization and enable the detection of nanoplastics [5]. Field-deployable sensors and real-time detection systems, such as portable Raman/FTIR units, microfluidic chips, and optofluidic sensors, support on-site monitoring in aquatic and terrestrial environments [6]. Additionally, specialized nanoplastic detection techniques like nanoparticle tracking analysis, dynamic light scattering, and asymmetric flow field-flow fractionation with multi-angle light scattering address the major challenge of identifying submicron particles that traditional methods cannot resolve [7].

Artificial intelligence (AI) and machine learning technologies provide transformative approaches to managing microplastics, encompassing detection, characterization, source identification, and remediation applications. Collectively, AI integration across the advanced detection technologies mentioned above enhances sensitivity, reduces subjectivity, enables high-throughput processing, and supports more standardized and reliable monitoring of micro- and nanoplastics. This editorial discusses recent advances and potential applications of AI in studying microplastic properties, transport, fate, and managing microplastic pollution.

2. Automated Detection and Characterization of Microplastics Using Deep Learning

Convolutional neural networks (CNNs) and image segmentation algorithms enable automated identification and classification of microplastics in optical and electron microscopy imagery, with recognition accuracy exceeding 85% [8]. These deep learning models extract morphological features including particle size, shape, color, and surface characteristics, effectively distinguishing microplastics from natural organic particles and cellular debris. The automated morphological analysis significantly reduces manual processing time from hours per sample to minutes, enabling high-throughput characterization of environmental samples. Advanced CNN architectures trained

on large image datasets overcome limitations of conventional pixel-based classification methods, capturing complex spatial patterns indicative of microplastic composition and degradation states [4, 9].

Spectroscopic data fusion with machine learning accelerates polymer identification in microplastic particles through Raman spectroscopy, FTIR spectroscopy, and near-infrared spectroscopy combined with classification algorithms [10]. Transfer learning approaches trained on spectroscopic reference databases enable rapid determination of polymer type without requiring extensive calibration procedures for individual measurement systems [11]. These hybrid spectroscopic-machine learning systems enable polymer identification within seconds, compared to manual spectral analysis, which requires specialized expertise. Support vector machines, random forests, and neural networks extract distinctive spectral signatures from microplastic samples, establishing quantitative relationships between measured optical properties and polymer composition while simultaneously reducing false positive identifications [12]. A summary of the AI techniques for microplastic characterization is shown in Table 1.

Table 1 AI Techniques for Microplastics Characterization.

Technique	Feature
Convolutional neural networks for morphological analysis	Automatically extract particle size, shape, color, and texture features from microscopy imagery, achieving classification accuracy exceeding 95% on benchmark datasets [13, 14]
Spectroscopic machine learning for polymer identification	Integrate Raman and infrared spectroscopy data with support vector machines and neural networks to classify polymer types rapidly and accurately [10, 11]
Image segmentation algorithms for particle delineation	Precisely separate microplastic particles from background matrices and adjacent particles using deep learning-based semantic segmentation [9]
Clustering algorithms for microplastics classification	Group microplastics by size distribution and compositional properties using k-means and hierarchical clustering on extracted deep features [15]

3. Source Identification and Microplastic Fate Modeling

Machine learning algorithms analyze microplastic composition, size distribution, and chemical additives to systematically identify generation sources, including tire wear, textile fibers, microbeads, and plastic fragmentation [16]. These algorithms extract distinctive morphological and spectroscopic signatures from environmental samples, enabling differentiation between primary microplastics from direct manufacturing and secondary microplastics resulting from the fragmentation of larger plastic items [8]. For instance, a study used three machine learning models, namely multilabel decision trees, random forests, and support vector machines, to trace microplastic sources in four wastewater treatment plants in Hong Kong, revealing that they primarily originated from domestic activities (57.3–59.9%), followed by industrial (21.1–21.7%), coastal (11.2–12.7%), domestic/medical (4.6–5.1%), and domestic/agricultural (2.6–3.8%) inputs (Figure 1) [17].

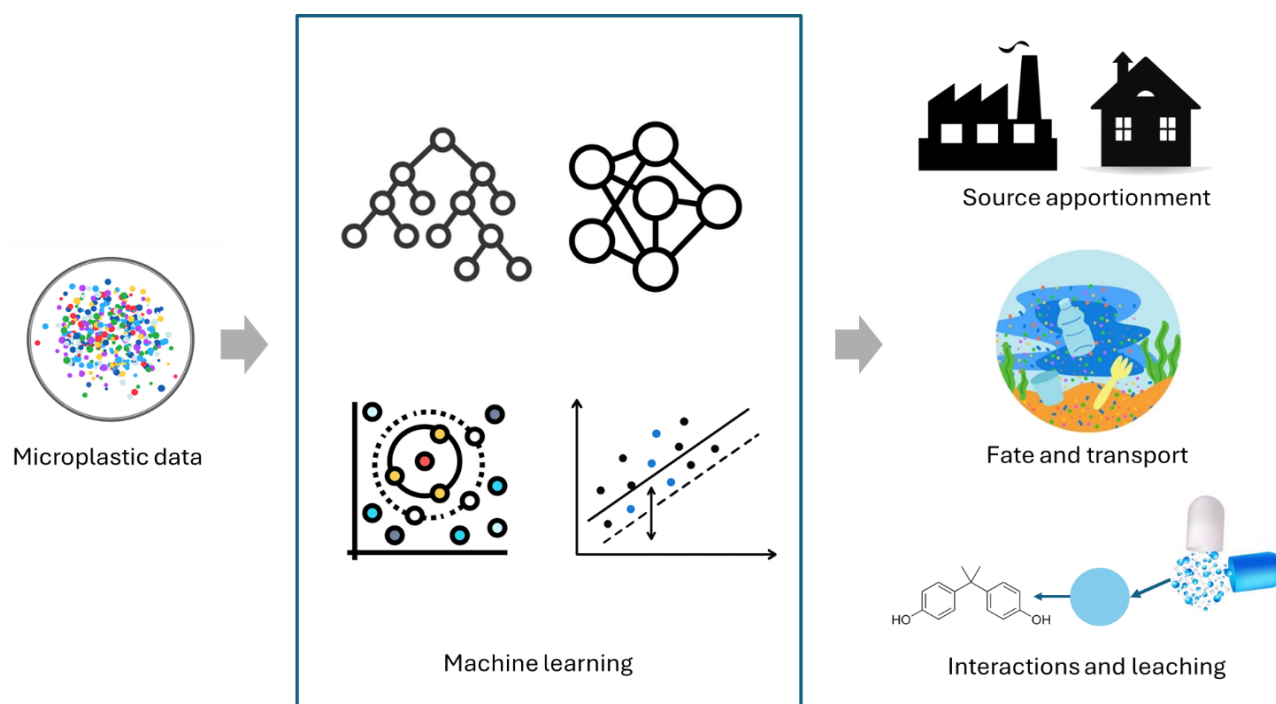


Figure 1 Applying AI to identify microplastic sources, analyze their fate, transport, and interactions.

Predictive models trained on reference microplastics from known sources enable the apportionment of sources in environmental samples, quantifying the relative contributions of different pollution pathways. This apportionment approach leverages morphological characteristics, such as fiber and bundle morphologies indicating textile sources, spherical particles suggesting personal care product origins, and irregular fragments denoting fragmentation processes, to assign environmental microplastics to their likely parent products and industrial processes [18]. By establishing quantitative relationships between particle characteristics and source origins, machine learning models provide evidence-based identification of dominant microplastic migration pathways within specific watersheds and urban environments.

AI-driven temporal and spatial modeling of microplastic transport and fate in aquatic environments integrates water quality parameters, hydrodynamic data, and microplastic concentration measurements to predict contamination patterns and identify accumulation zones (Figure 1) [19]. These spatiotemporal neural networks capture the complex interactions between water flow, particle settling velocity, density-dependent transport, and biofilm colonization, which affect the fate of microplastics in rivers and coastal waters. Machine learning models trained on historical monitoring data and environmental conditions enable forecasting of microplastic concentrations at downstream locations and prediction of contamination events triggered by high-flow events or industrial releases [20]. Specifically, Fazil et al. [21] employed machine learning to predict microplastic transport in laboratory open-channel experiments under various flow conditions, vegetation patterns, and particle densities. Four machine learning models, including Random Forest, Decision Tree, Extreme Gradient Boost (XGB), and K-Nearest Neighbor, were trained on 75% of the dataset and validated on the remaining 25%, with performance compared to a linear regression model. All machine learning models outperformed linear regression, and XGB and Random Forest delivered the highest prediction accuracy. Additionally, Hu et al. [22] proposed

a new spatiotemporal graph neural network to analyze how river hydrodynamics shape microplastic transport, which outperformed traditional numerical approaches, achieving correlation coefficients above 0.89 (vs. 0.6–0.7) when validated with field data from multiple monitoring sites. It also reduced computational time by about 92% while delivering similar accuracy.

AI has also been increasingly used to predict the interactions between microplastics and other pollutants (Figure 1). AI can predict how pollutants bind to or release from microplastic surfaces by learning from experimental data on hydrophobicity, functional groups, weathering-induced surface oxidation, and particle roughness. Models such as XGB and Support Vector Regression can forecast adsorption coefficients (e.g., K_d , K_{oc}) more accurately than traditional isotherm models. A study built and trained a machine learning model using 303 datasets from open-access studies [23]. After testing multiple single, ensemble, and deep learning approaches, a tree-based stacking model delivered the best results, with an R^2 of 0.91 and a root mean square error (RMSE) of 0.12. Another study employed models using ATR-FTIR spectra to estimate individual and total adsorption capacities (q_e) of 192 microplastics for pharmaceutical and personal care products [24]. Using maximal information coefficient analysis and gradient boosting decision tree regression, the models achieved high accuracy, with R^2 values of 0.9772 and 0.9661 during training.

Since plastics contain various additives, the leaching of chemicals from microplastics is another area of concern [25]. AI has demonstrated the ability to predict these leaching behaviors (Figure 1). A study used multiple regression, artificial neural networks (ANN), support vector machines, and random forest regression to predict leaching of plasticizers and other contaminants from microplastics, based on gas chromatography-mass spectrometry data [26]. ANN and support vector machines showed strong predictive performance, with correlation coefficients of 0.96–0.98 and 0.93–0.99, respectively, while multiple regression performed poorly ($R^2 = 0.03$ –0.24) for plastic phthalate esters.

4. Microplastics Removal and Remediation Optimization Through AI

With the ability to predict the interactions between microplastics and other environmental pollutants, machine learning models demonstrate the potential to model adsorption capacity and removal efficiency of microplastics on activated carbon and other adsorbent materials by integrating surface property data, environmental parameters, and compositional variables to optimize material design. This domain remains to be further explored.

AI-driven optimization of wastewater treatment processes identifies the ideal conditions for removing microplastics through integrated filtration, coagulation, and advanced oxidation pathways. This potential was demonstrated in a study that tested the removal of polystyrene microplastics in synthetic water using different doses of FeCl_3 and chitosan under varying pH levels, mixing speeds, and settling times [27]. FeCl_3 removed about 89.3% of polystyrene, while chitosan removed 21.4%, and their combined use achieved up to 99.8% removal under optimal conditions (2 mg/L FeCl_3 , 7 mg/L chitosan, pH 6.3, 100 rpm, 30 min). An ANN closely matched the experimental outcomes, yielding an RMSE of 1.0643 and an R^2 of 0.9997.

Reinforcement learning algorithms can optimize membrane filtration and electrochemical treatment systems for microplastics removal through adaptive real-time control mechanisms. While still in its infancy, preliminary work has combined experiments with ANN modeling to examine how five overlooked microplastics are removed during coagulation–ultrafiltration treatment [28].

Coagulation alone removed 37.0–56.0% of the particles, while ultrafiltration eliminated nearly all remaining microplastics. Five ANN models were developed and refined using activation function tuning and batch normalization, achieving highly accurate predictions with R^2 values between 0.9972 and 0.9987.

5. AI-Enabled Assessment of Ecological and Human Health Impacts of Microplastics

Machine learning models can potentially integrate microplastic exposure data with biological endpoints to quantify toxicological effects on aquatic organisms, including fish, crustaceans, and invertebrate communities. These toxicity prediction systems incorporate exposure duration, particle size, environmental conditions, and species-specific ecological traits to forecast population-level consequences of microplastic contamination under different pollution scenarios [29]. A machine-learning framework was created to classify the cytotoxicity of micro- and nanoplastics using 1,824 data points compiled from the literature and described by nine physicochemical, biological, and experimental features [30]. The full decision-tree ensemble model achieved high performance (accuracy 0.95; recall and precision 0.86). After feature selection, a reduced model using six key variables produced similarly strong predictive results.

Another study investigated whether AI, specifically large language models such as ChatGPT and Gemini, can aid in standardizing QA/QC screening in microplastic research [31]. Using prompts built from established QA/QC criteria for drinking water studies, the models evaluated 73 publications from 2011 to 2024. The AI tools efficiently extracted key information, judged study reliability, and closely matched human assessments. Results show that large language models can greatly improve the speed, consistency, and usefulness of QA/QC evaluations, supporting stronger exposure and risk assessments and helping harmonize microplastic research within regulatory contexts. Additionally, Zhang et al. [32] created an ensemble machine-learning model to predict the joint toxicity (survival rates) of micro/nanoplastics and pollutants across different species. The model showed strong predictive power in both cross-validation and external tests ($R^2 > 0.84$). Model interpretation revealed that combined toxicity is mainly driven by pollutant concentration, organism type, pollutant class, and plastic particle size.

Liu et al. [33] applied six machine learning algorithms to quantitative structure-activity relationship (QSAR)-based predictions of microplastic toxicity on BEAS-2B cells. XGB performed best ($R^2_{\text{train}} = 0.9876$, $R^2_{\text{test}} = 0.9286$). Williams' plot analysis confirmed stable predictions within the applicability domain. Feature importance analyses (Embedded Feature Importance, Recursive Feature Elimination, SHAP) consistently highlighted particle size as the key factor influencing toxicity.

6. Potential Future AI Applications in Microplastic Pollution Management

Machine learning may enable integrated assessment models to simulate complex interactions between microplastics generation, transport, fate, ecological impacts, and human health outcomes, informing comprehensive policy frameworks [8]. These coupled system models incorporate data from source emission inventories, environmental fate models, ecological toxicity databases, and epidemiological studies to forecast long-term consequences of alternative policy scenarios. The integration of supply chain data with circular economy models identifies opportunities for extended producer responsibility, design-for-durability innovations, and material substitution that prevent

microplastic generation at source, rather than addressing environmental accumulation through downstream remediation [34].

The emergence of AI-powered microplastic sensors may facilitate real-time monitoring of microplastics in different environmental media. Sarker et al. [35] presented a computer vision and AI approach for microplastic detection using three camera systems (fixed-focus 2D and autofocus 2D/3D). A YOLOv5 model identified microplastics in images, while DeepSORT tracked them across frames. Real-time tests achieved high precision in counting, with 97% accuracy in the lab and 96% in a river field setting. Seggio et al. [36] developed an AI-enabled sensing approach to detect nano- and microplastics by analyzing how samples interact with an estrogen receptor–modified gold surface on a low-cost plastic optical fiber surface plasmon resonance platform. Machine-learning models trained on particles of different sizes and materials enabled the sensor to distinguish polystyrene and poly (methyl methacrylate) particles (20 μm and 100 nm) with 90.3% accuracy, demonstrating a proof-of-concept “smart” interface for particle identification. Huang et al. [37] developed a liquid–solid triboelectric nanogenerator (LS-TENG) paired with a deep learning model to detect and classify microplastics in liquids. Different types and concentrations of microplastics strongly affected the LS-TENG voltage signal, which showed a linear response to microplastic content between 0.025% and 0.25% wt%. Using these signals, a convolutional neural network accurately identified microplastic types, enabling both quantitative detection and classification of microplastics.

The maturation of AI-enabled sensors will soon enable studies that embed them into manufacturing lines and wastewater treatment systems, allowing for continuous real-time detection of microplastics. These sensors, whether based on optical fibers, triboelectric signals, computer vision, or spectroscopic signatures, allow AI models to instantly identify spikes in microplastic release, determine particle types, and pinpoint their sources. With this information, AI can automatically adjust industrial operations by modifying washing, filtration, or extrusion conditions, predicting equipment failures that cause shedding, or triggering rapid interventions to prevent microplastic leakage at the source.

In wastewater treatment plants, AI integrates sensor data with process controls to optimize coagulation, flocculation, sedimentation, and membrane filtration, ensuring high removal efficiency even under fluctuating loads. AI can fine-tune chemical dosing, prevent membrane fouling, and redirect high-microplastic influent to advanced treatment units, while creating a feedback loop that continuously improves system performance [38]. Together, these AI-driven solutions transform microplastic management from a passive monitoring practice to an automated, predictive, and highly efficient strategy for reducing pollution.

7. Limitations

Despite its rapidly expanding applications, AI in microplastics research faces several limitations that constrain its reliability and real-world deployment. Most models rely on large, high-quality, and well-annotated datasets; however, microplastic imagery, spectroscopic libraries, and toxicity data remain fragmented, inconsistent, and biased toward specific polymers, sizes, and environmental conditions. As a result, AI systems trained on controlled laboratory datasets often perform poorly when exposed to weathered, biofouled, irregular, or environmentally mixed particles [39]. Many deep learning and spectroscopic models also operate as “black boxes,” offering limited

interpretability for regulatory use and risk assessment. Variability in sampling methods, imaging conditions, and instrumental settings leads to reduced model transferability across laboratories and monitoring programs [9]. In environmental modeling, AI struggles to capture complex, multiscale hydrodynamic processes, and predictions can fail when applied to new watersheds or extreme events [20]. Finally, without standardized QA/QC frameworks, AI-generated classifications, polymer identifications, or toxicity predictions risk introducing systematic errors into microplastic assessments, limiting their acceptance in policy, regulation, and environmental management [31].

Author Contributions

The author solely contributed to the writing of this editorial.

Competing Interests

The author has declared that no competing interests exist.

AI-Assisted Technologies Statement

Grammarly was used for language editing during the manuscript writing process, including grammar, punctuation, and stylistic refinement.

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