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Artificial intelligence for modeling and reducing microplastic in marine environments: A review of current evidence

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ABSTRACT

Marine microplastic pollution presents a critical environmental challenge, affecting ecosystems, wildlife, and human health as millions of tons of plastic waste enter oceans each year. Microplastics, due to their small size, are difficult to detect and accumulate widely in marine environments, where they integrate into the food web. Artificial Intelligence (AI) offers promising advancements for modeling, detecting, and mitigating the effects of microplastics in marine ecosystems. This narrative review examines recent developments in AI applications for addressing microplastic pollution. The review focuses on AI-driven modeling for predicting microplastic flows, intelligent waste detection systems that utilize remote sensing and autonomous robotics, and AI-based interventions aimed at reducing microplastic release. AI-driven models enhance the accuracy of predicting microplastic accumulation zones, supporting targeted clean-up efforts and informed policy-making. Advanced detection systems provide real-time monitoring over extensive areas, while AI-based filtration and material innovation technologies help reduce microplastic pollution at the source. AI holds significant potential to mitigate marine microplastic pollution, yet challenges such as data availability, model refinement, and global collaboration remain. Future research should focus on enhancing AI models, refining detection systems, and encouraging international data-sharing and cooperation. Collaboration across sectors is essential to fully leverage AI's potential in safeguarding marine ecosystems from microplastic pollution.

Abbreviations

AI	Artificial Intelligence
ML	Machine Learning
AUV	Autonomous Underwater Vehicle
ROV	Remotely Operated Vehicle
PVC	Polyvinyl Chloride
BPA	Bisphenol A
PS	Polystyrene P
LA	Polylactic Acid
VOCs	Volatile Organic Compounds
SDG	Sustainable Development Goals
MARPOL	International Convention for the Prevention of Pollution from Ships
UNEA	United Nations Environment Assembly
TRL	Technology Readiness Level
GOOS	Global Ocean Observing System
UNEP	United Nations Environment Programme

1. Introduction

Marine microplastic pollution has become an escalating environmental challenge over the past few decades, impacting ecosystems, wildlife, and human health. Microplastics, which are plastic particles smaller than 5 mm, are generated from various sources, including the degradation of larger plastic debris, synthetic fibers from textiles, and even personal care products such as cosmetics (Megha et al., 2024; Shi et al., 2023). These tiny particles are introduced into the oceans through

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runoff, improper waste management, and atmospheric deposition, among other pathways (Raju et al., 2023). Once they enter marine environments, microplastics persist for extended periods due to their resistance to natural degradation processes (Maddison et al., 2023). As a result, they accumulate in water bodies, sediments, and even marine organisms, posing significant threats to aquatic ecosystems and the broader food web, including human populations that consume seafood.

The pervasive nature of microplastic pollution is well-documented, with reports finding these particles in the deepest parts of the oceans and even in remote polar regions. Marine organisms, from plankton to larger species like fish, seabirds, and whales, inadvertently ingest microplastics, mistaking them for food (Terrazas-López et al., 2024). This ingestion not only leads to physical harm but also introduces harmful chemicals attached to microplastics into the food chain. The ecological consequences are staggering, as microplastic ingestion can lead to reduced reproductive success, stunted growth, and even mortality in marine species (Bhat et al., 2024). Furthermore, as these plastics accumulate in the food web, humans are increasingly exposed to microplastics through the consumption of seafood, raising concerns about potential health risks such as inflammation and toxicity (Unuofin and Igwaran, 2023).

Addressing microplastic pollution requires an innovative, multidisciplinary approach due to its complexity and global scale. Traditional methods for managing plastic waste, such as recycling and waste collection, have proven insufficient, as they focus on the removal of larger plastic debris while microplastics continue to evade detection and removal (Thacharodi et al., 2024). Thus, there is a growing need for advanced technological solutions that can more effectively monitor, model, and mitigate microplastic pollution (Thacharodi et al., 2024). Among the emerging technologies, Artificial Intelligence (AI) stands out as a powerful tool with the potential to revolutionize how we tackle this environmental crisis.

AI is well-suited to address the challenges posed by marine microplastics, thanks to its ability to analyze large datasets, detect patterns, and generate predictive models that traditional methods cannot achieve. One of AI's key strengths is its capacity to model microplastic flows in the ocean. Using oceanographic data such as currents, wind patterns, and temperature, AI models can predict the movement of microplastics from their sources to accumulation zones (Chubarenko et al., 2024). These predictions allow scientists to identify high-risk areas, or hotspots, where microplastic pollution is likely to concentrate, such as ocean gyres or coastal areas near urban centers. By modeling these flows with higher accuracy, AI can guide cleanup efforts, policy interventions, and international cooperation aimed at preventing further pollution (Guo et al., 2024).

In addition to modeling, AI-driven detection systems are being developed to track microplastics in real time. Traditional methods of detecting microplastics, such as water sampling and laboratory analysis, are time-consuming, costly, and often limited in scope (Zhu et al., 2024). AI-powered tools, on the other hand, can process data from satellite imagery, underwater sensors, and even drones to detect microplastics across vast areas of the ocean (Jin et al., 2024). For example, machine learning algorithms can be trained to recognize the spectral signatures of microplastics, enabling automated detection from remote sensing data. Autonomous underwater vehicles (AUVs) equipped with AI technologies can also sample water and detect microplastic concentrations at different ocean depths, providing a more comprehensive understanding of pollution distribution (Farré, 2020a, 2020b).

Beyond detection, AI offers immense potential for mitigating the environmental impacts of microplastic waste. AI-driven interventions, such as optimizing waste management systems or guiding the design of biodegradable materials, could help reduce the release of microplastics into the marine environment (Kuusisto, 2024). For instance, AI can optimize recycling and waste collection routes to reduce the likelihood of plastics reaching the oceans. Additionally, AI can aid in the development of advanced filtration systems for wastewater treatment plants, which are known sources of microplastic emissions (Jiang et al., 2020). By enhancing the efficiency of these systems, AI can play a critical role in capturing microplastics before they enter water bodies, thereby reducing their environmental footprint.

The rationale for this narrative review stems from the urgent need to address the growing environmental threat posed by marine microplastic pollution, which has significant ecological and health consequences. Given the limitations of traditional methods in tracking, modeling, and mitigating microplastics, it is crucial to explore innovative approaches like AI that offer more efficient and scalable solutions. The objective of this review is to comprehensively assess the potential of AI in modeling microplastic flows, detecting waste in marine environments, and driving AI-powered interventions to reduce the environmental impact of microplastic pollution. By synthesizing current research and applications of AI in this field, the review aims to provide a clearer understanding of how AI technologies can be leveraged to enhance marine conservation efforts and inform future research and policy development in combating microplastic pollution.

Despite growing interest in applying AI technologies to environmental monitoring, several critical gaps remain in the current body of research on AI-driven microplastic pollution management. First, existing AI models for microplastic flow prediction often rely on limited datasets with geographic biases, predominantly from well-monitored regions in developed countries, while vast oceanic areas and coastal zones in developing nations remain underrepresented (Brander et al., 2020). This geographic data inequality compromises the global applicability of predictive models and limits their effectiveness in regions most vulnerable to marine pollution.

Second, there is a lack of systematic comparison and standardization of AI algorithms used for microplastic detection and quantification. Current literature presents various machine learning approaches, from convolutional neural networks to support vector machines, without comprehensive benchmarking of their relative performance, accuracy rates, computational costs, and suitability for different environmental conditions (Hu et al., 2024; Su et al., 2023). This absence of standardized evaluation frameworks makes it difficult for researchers and practitioners to select optimal AI solutions for specific applications.

Third, the integration of AI technologies with existing regulatory frameworks and international maritime policies remains poorly explored. While technical capabilities advance rapidly, the pathway from AI-driven insights to actionable policy interventions and compliance monitoring systems is insufficiently mapped (Wu, 2020). Additionally, the technological readiness levels (TRL) of various AI applications vary widely, yet few studies provide realistic assessments of implementation barriers, scaling challenges, and the resource disparities between high-income and low-income countries. Finally, current reviews predominantly focus on technical capabilities without adequately addressing the socio-economic dimensions of AI deployment, including implementation costs, capacity-building requirements, and ethical considerations related to data sovereignty and equitable access to advanced monitoring technologies.

Furthermore, while several recent reviews have examined AI applications in marine environmental monitoring (Zhao et al., 2024; Su et al., 2023), most existing reviews focus narrowly on individual AI techniques

Table 1
Estimated quantities of microplastics entering the marine environment annually (in kilotonnes).

Category	(Boucher, 2017)	(United Nations Environment Programme (UNEP) and UNEP, 2018)	(Pew Charitable Trust, 2020).	(Paruta et al., 2021)	(Jambeck et al., 2015)	(Organisation for Economic Co-operation and Development (OECD), 2022)	(Ryberg et al., 2019)	Earth Action (Cózar et al., 2014)	Average Quantity	Standard Deviation
Personal Care Products	30	10	200	–	–	–	10.963	36	57	80.54
Pellets	5	30	200		–	432	9	848	254	334.58
Paint	156	–	–	1900	–	–	–	1846	1301	991.68
Synthetic Textiles	522	260	40	–	–	135	219	88	211	172.82
Tires	424	1410	1000	–	–	648	1410	946	973	397.60
Macroplastics (Becoming Microplastics)		5270	11,000	–	4800–12,700 (8000)	6000	–	–	7568	2562.85

or specific applications without providing an integrated perspective on how these technologies can work synergistically. Unlike previous reviews that primarily catalog AI methods or focus exclusively on detection algorithms, this review uniquely integrates three critical dimensions: (1) the technical capabilities across the full AI application spectrum from modeling to intervention, (2) the practical implementation challenges including computational requirements, regulatory alignment, and economic feasibility, and (3) the equity considerations in global deployment. Moreover, while earlier reviews have documented AI's potential in microplastic research, they have not systematically addressed the critical gap between prototype demonstration and operational deployment, nor have they provided structured frameworks for integrating disparate AI components into unified monitoring and management systems. This review addresses these limitations by presenting a comprehensive synthesis that bridges technical innovation with practical implementation pathways and explicitly addresses the geopolitical and socioeconomic dimensions that determine whether AI advances translate into meaningful environmental outcomes.

This review addresses these gaps by: (1) providing a systematic classification of AI methodologies for microplastic management based on their functional applications, flow prediction, detection systems, and intervention technologies; (2) critically evaluating the current state of technology readiness and implementation barriers; (3) explicitly linking AI capabilities to international policy frameworks including MARPOL Annex V, UNEA resolutions, and SDG 14; (4) assessing the disparity in AI adoption between developed and developing nations; and (5) proposing a comprehensive research agenda that integrates technical advancement with policy implementation, capacity building, and equitable global access to AI-driven marine pollution management tools.

Table 1 shows various publications reports on the principal sources of microplastics and their respective contributions in kilotonnes. Macroplastics, which eventually disintegrate into microplastics, contribute significantly to annual ocean leakage. It should be noted that each study used various methodology; where possible, the range is provided with a central value.

2. Review methodology

This narrative review systematically examined current evidence on AI applications for modeling and reducing microplastic pollution in marine environments. The review methodology followed a structured approach to ensure comprehensive coverage while maintaining flexibility to capture emerging technologies and interdisciplinary insights.

2.1. Search strategy

A comprehensive literature search was conducted across multiple electronic databases including Web of Science (Core Collection), Scopus, PubMed/MEDLINE, IEEE Xplore Digital Library, and Google Scholar for grey literature and emerging preprints. The search encompassed publications from January 2015 to October 2025 to capture both foundational work and recent technological advances.

Search terms *combined three conceptual domains. The first domain focused on microplastics using terms such as "microplastic" OR "micro-plastic*" OR "plastic debris" OR "marine plastic pollution" OR "oceanic plastic". The second domain addressed artificial intelligence using terms including "artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "computer vision" OR "predictive model*" OR "AI" OR "ML". The third domain covered application contexts with terms such as "ocean*" OR "marine" OR "sea" OR "aquatic" OR "detection" OR "monitoring" OR "prediction" OR "modeling" OR "remediation". The final search string combined all three domains using Boolean operators: (Domain 1) AND (Domain 2) AND (Domain 3)

2.2. Inclusion and exclusion criteria

Studies were included if they were peer-reviewed journal articles, conference proceedings, or authoritative technical reports describing AI applications for microplastic detection, modeling, flow prediction, or intervention technologies. Additionally, research on remote sensing, image recognition, autonomous systems, and predictive analytics for marine microplastics was included. Publications had to be in English and provide sufficient methodological detail to assess the AI approach and outcomes.

Studies were excluded if they focused solely on microplastic characterization without AI components, were reviews without original synthesis or conceptual frameworks, addressed terrestrial or freshwater systems without marine relevance, were opinion pieces and editorials without empirical foundation, or were duplicate publications and conference abstracts later published as full articles.

2.3. Selection process

The selection process followed four stages. Initial screening involved reviewing titles and abstracts against inclusion criteria. Full-text assessment then evaluated complete articles for relevance and quality. Supplementary searching through reference lists of key articles and forward citation tracking identified additional relevant studies. Final inclusion resulted in a corpus of studies that formed the basis of this synthesis.

2.4. Data extraction and synthesis

Information extracted from included studies comprised AI methodology type including machine learning algorithms, deep learning architectures, and computer vision systems. Application domains such as flow prediction, detection systems, and intervention technologies were documented, along with environmental contexts covering surface waters, water column, deep sea, and coastal areas. Data sources including satellite imagery, AUVs, water sampling, and sensors were noted. Performance metrics such as accuracy, precision, and computational efficiency were recorded, alongside implementation challenges, limitations, policy implications, and scalability considerations.

Given the heterogeneity of AI applications and methodologies, a narrative synthesis approach was adopted rather than meta-analysis. Studies were grouped thematically according to their primary function: AI for modeling microplastic flows and accumulation, intelligent waste detection systems, and AI-driven interventions to minimize environmental impact. Within each theme, findings were synthesized to identify patterns, assess technological maturity, and highlight knowledge gaps.

2.5. Quality assessment

While formal quality scoring was not applied given the review's narrative nature and technological focus, studies were evaluated for methodological rigor and transparency, reproducibility of AI approaches, validation procedures and performance benchmarking, acknowledgment of limitations, and relevance to real-world implementation.

2.6. Limitations of review methodology

This review has several important limitations that should be acknowledged. As a narrative review, this work does not follow the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, which are typically applied to systematic reviews with quantitative meta-analysis. The narrative approach was chosen due to the heterogeneity of AI applications, the diversity of methodologies across studies, and the rapidly evolving nature of the technology landscape, which makes standardized quantitative synthesis challenging. This methodological choice allows for broader thematic synthesis and conceptual framework development but lacks the structured reporting and bias assessment protocols of systematic reviews.

The rapidly evolving nature of AI technology means that very recent developments may not yet appear in peer-reviewed literature, potentially leading to an incomplete picture of cutting-edge capabilities. The predominance of English-language publications may have excluded relevant work published in other languages, introducing potential language bias. The lack of standardized reporting practices in AI-marine science applications complicated direct comparisons across studies, as different research teams use varying metrics, datasets, and validation approaches. Publication bias may favor studies reporting successful AI implementations over those documenting challenges or failures, potentially leading to an optimistic assessment of current capabilities. Geographic concentration of research in well-resourced institutions may result in underrepresentation of perspectives and challenges from developing nations. Finally, the interdisciplinary nature of this field, spanning computer science, oceanography, environmental science, and policy, means that relevant work may be scattered across discipline-specific literature that traditional search strategies might not fully capture.

3. The scope of microplastic pollution in marine environments

Marine ecosystems are facing an unprecedented influx of plastic waste, with approximately 8 million tons of plastic entering the oceans annually (Sharma et al., 2023). This massive volume of plastic waste, driven by rapid industrialization, urbanization, and inadequate waste management practices, has far-reaching consequences for marine biodiversity and ecological balance. Over time, larger plastic debris breaks down into smaller fragments, resulting in the formation of microplastics, plastic particles smaller than 5 mm, which are particularly difficult to track and remove due to their size (Born et al., 2023). Recent studies have highlighted the alarming presence of microplastics in almost every marine environment, from surface waters and deep ocean trenches to polar ice caps (Petersen and Hubbart, 2020). Even the most remote areas, far removed from human activities, have shown evidence of microplastic contamination (Padha et al., 2021). The persistence of microplastics in marine environments is particularly concerning because these particles resist natural degradation processes, potentially remaining in the ecosystem for centuries. This long-term presence, combined with the continuous influx of new plastic waste, leads to the accumulation of microplastics in marine ecosystems, posing threats to the health of aquatic species, ecosystems, and ultimately humans.

3.1. Biological impacts: ingestion and bioaccumulation

One of the most significant concerns regarding microplastic pollution is its ability to infiltrate the marine food web. The small size of microplastics allows them to be ingested by a wide range of marine organisms, from the smallest zooplankton to larger species such as fish, sea turtles, and whales. A growing body of evidence indicates that microplastic ingestion has direct negative effects on marine life, leading to physical harm, nutritional deficiencies, and even death (Thacharodi et al., 2023). For example, fish and seabirds that consume microplastics may experience reduced feeding efficiency and impaired digestive function due to plastic accumulation in their gastrointestinal tracts. Moreover, the toxic chemicals associated with plastics, such as phthalates and bisphenol A (BPA), can leach into the tissues of organisms, causing further physiological harm (Premalatha and Kumari, 2024).

Bioaccumulation of microplastics through the food chain is another critical issue. When smaller organisms ingest microplastics, they are consumed by larger predators, leading to the accumulation of these particles at higher trophic levels (McHale and Sheehan, 2024). This bioaccumulation has potential health risks not only for marine species but also for humans, who may consume seafood contaminated with microplastics. A study found that microplastics have been detected in human blood and tissues, raising concerns about long-term exposure and the potential for chronic health effects, such as inflammation, immune system disruption, and toxicity.

Table 2 summarizes the impact of microplastic exposure on several organoids. After one week, polyester fibers in airway organoids reduced biomarkers of pulmonary health, indicating lung injury. With prolonged exposure to polystyrene (PS), forebrain organoids demonstrated developmental problems and decreased cell viability. Intestinal organoids accumulated PS, causing cell death and inflammation primarily through endocytosis. Liver organoids treated to PS showed altered lipid metabolism and elevated stress indicators, indicating hepatotoxicity.

Fig. 1 depicts the various applications of bioplastics, which are made from renewable biological sources such starch, cellulose, and polylactic acid (PLA). These materials are increasingly being used in consumer

Table 2
Characteristic studies on microplastics exposure using human organoids.

Organoid Type	Microplastic Type and Source	Exposure Conditions	Toxic Effects	Reference
Airway Organoids	Polyester fibers from synthetic clothes and fabrics, 700 ± 400 µm	1, 10, and 50 µg/mL for 1 week	Fibers penetrate the cellular layer, resulting in a substantial drop in SCGB1A1 gene expression, a lung damage biomarker.	Winkler et al., 2022
Forebrain Organoids	Polystyrene (PS), 1, 10 µm	5, 50, and 100 µg/mL for 7 and 27 days	Long-term Polystyrene exposure lowers cell viability and inhibits embryonic brain-like tissue development.	Hua et al., 2022
Intestinal Organoids	Polystyrene (PS), 50 nm	10 and 100 µg/mL for 1 and 2 days	Accumulation in numerous intestinal cells promotes cell death and inflammation, and endocytosis is critical for absorption	Hou et al., 2022
Liver Organoids	Polystyrene (PS), 1 µm	0.25, 2.5, and 25 µg/mL for 48 h	Causes hepatotoxicity, alters lipid metabolism, and elevates HNF4A and CYP2E1 levels in liver organoids particularly.	Cheng et al., 2022

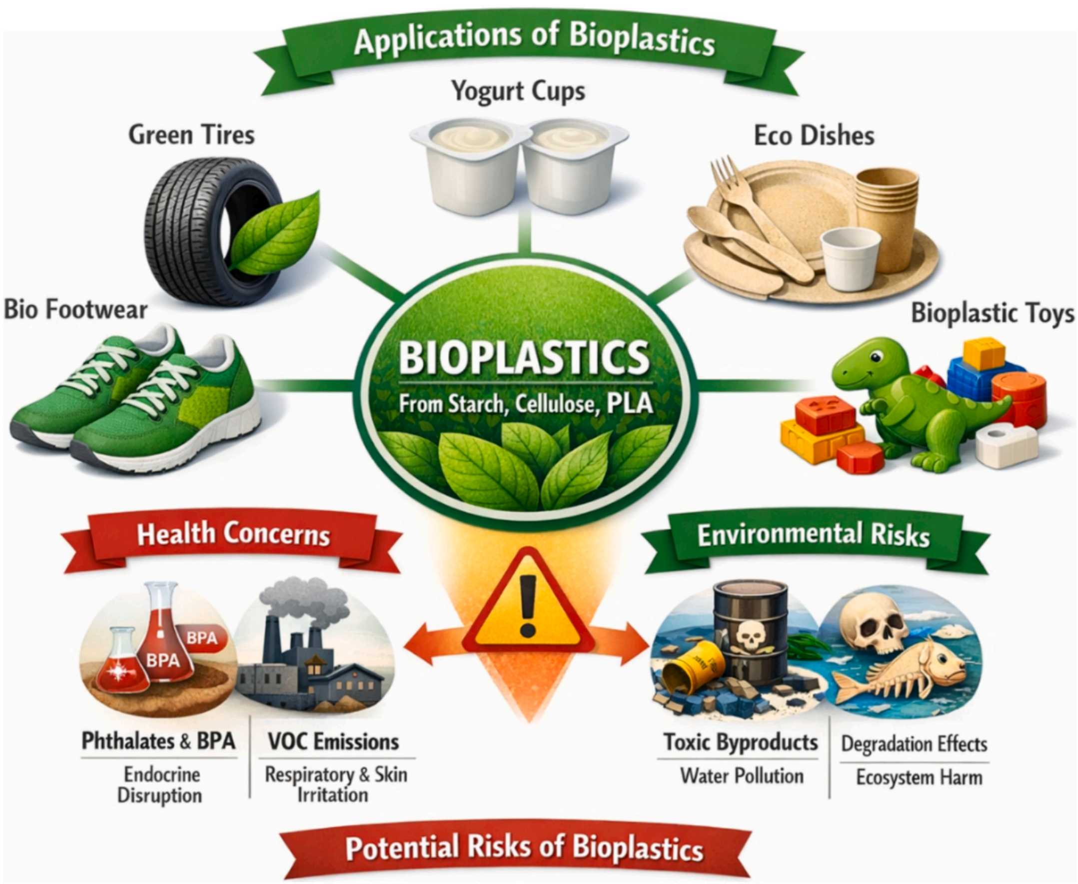

Fig. 1. Representation of the sources and biological effect of microplastics.

products such as tires, yogurt cups, throwaway dishes, footwear, and toys. Despite their environmental benefits over standard plastics, bioplastics may pose health issues due to specific additives and degradation byproducts. Certain bioplastics, for example, may contain phthalates or BPA, both of which have been related to endocrine disruption and reproductive damage. Furthermore, during processing or degradation, they may emit volatile organic compounds (VOCs) that irritate the respiratory system and skin, as well as toxic substances into aquatic environments, raising concerns about their potential effects on human health and ecosystems.

3.2. Sources of microplastic pollution

The sources of microplastic pollution are varied, making it challenging to manage and reduce its spread. Microplastics are classified into two categories based on their origin: primary microplastics and secondary microplastics. Primary Microplastics are intentionally manufactured small plastic particles used in various consumer products and industrial applications. For instance, microbeads are added to cosmetics and personal care products like exfoliating scrubs, toothpaste, and cleansers (Kukkola et al., 2024). In addition, industrial abrasives used in processes such as sandblasting contribute to the release of primary microplastics into the environment (Bamigboye et al., 2024). Another major source of primary microplastics is the shedding of synthetic fibers from textiles during washing. A study by Akyildiz et al., 2024 estimated that around 35% of primary microplastics in the ocean originate from synthetic fibers, highlighting the significant role of the fashion and textile industries in marine pollution. Secondary Microplastics are the result of the fragmentation and degradation of larger plastic debris, such as plastic bags, bottles, and fishing nets (Idowu et al., 2024). Exposure to environmental factors like UV radiation, wind, and wave action causes these larger plastic items to break down into smaller particles over time. Secondary microplastics are more difficult to control because their generation is an inevitable consequence of the presence of macroplastics in marine environments. For example, discarded fishing gear, known as "ghost gear," is a substantial source of secondary microplastics, particularly in coastal areas and open seas.

3.3. Distribution and pathways of microplastics

Microplastics are highly mobile in marine environments, moving between water columns, sediments, and biological systems. Ocean currents, wind, and waves facilitate the widespread distribution of microplastics, allowing them to travel vast distances from their original source. For example, study conducted by Mountford and Maqueda, 2020, found that microplastics originating from densely populated regions are transported via oceanic gyres, accumulating in these remote areas. Similarly, the Great Pacific Garbage Patch, located in the North Pacific Ocean, has become a well-known microplastic accumulation zone due to the convergence of several major ocean currents. The movement of microplastics between marine environments is influenced by factors such as particle size, density, and buoyancy. Lighter microplastics, such as polyethylene and polypropylene, tend to float near the ocean surface, while denser particles like polyvinyl chloride (PVC) are more likely to sink into the ocean depths (Strafella et al., 2022). The vertical distribution of microplastics within the water column also varies, with particles becoming trapped in marine snow (organic matter falling from the surface to the seafloor), further complicating detection efforts.

Microplastic contamination is not confined to open ocean waters. Coastal environments, estuaries, and rivers are major entry points for microplastics, as land-based sources such as wastewater, stormwater runoff, and industrial discharges flow into these ecosystems. According to a study, rivers transport an estimated 1.15 to 2.41 million metric tons of plastic waste into the ocean each year, much of which is eventually broken down into microplastics (Simon, 2023). Moreover, wastewater treatment plants have been identified as significant contributors to microplastic pollution, as they are not fully equipped to filter out microplastics from effluent, leading to their release into rivers and oceans.

Fig. 2 depicts the mechanisms by which plastics enter the ocean and degrade into microplastics. Plastic contamination originates in industrial effluent, coastal areas, and untreated wastewater. Once in the water, plastics are classified as main or secondary. Primary plastics, such microbeads, reach the water as microplastics. Secondary plastics, like bigger debris, dissolve into microplastics over time, which is increased by UV exposure and other conditions in the water.

3.4. Challenges in modeling and mitigating microplastic pollution

The diverse sources, pathways, and persistence of microplastics in the marine environment present significant challenges for researchers and policymakers trying to model and mitigate the spread of these pollutants. Effective intervention strategies require an in-depth understanding of the lifecycle of microplastics, from their origin and movement in marine ecosystems to their interactions with living organisms and eventual degradation (Hajjar et al., 2023). However, the complexity of ocean systems, combined with the wide range of plastic materials and environmental variables, makes it difficult to predict where microplastics will accumulate and what their long-term effects will be. Traditional environmental models, which rely on physical and chemical principles, have struggled to capture the intricate behavior of microplastics in the ocean. These models are often limited by the availability of comprehensive data on plastic inputs, degradation rates, and transport mechanisms. As a result, they may provide inaccurate predictions of microplastic accumulation zones or fail to account for the interactions between microplastics and biological systems.

The variability in microplastic characteristics, such as particle size, shape, and density, adds another layer of complexity to modeling efforts. Different types of microplastics behave differently in the environment, with some remaining buoyant at the surface while others sink or become suspended in the water column. Additionally, the influence of external factors, such as ocean currents, wind patterns, and temperature fluctuations, further complicates the prediction of microplastic movement. Considering these challenges, there is a growing recognition of the need for more sophisticated tools and technologies to address the global microplastic pollution crisis. Advanced modeling techniques that incorporate real-time data, machine learning algorithms, and remote sensing technologies could significantly improve our ability to track, predict, and ultimately reduce microplastic pollution in marine environments (Phan and Luscombe, 2023).

4. AI for modeling microplastic flows and accumulation

AI offers transformative potential in understanding and mitigating microplastic pollution in marine environments, particularly through the development of sophisticated modeling systems. Traditional

Fig. 2. Graphical representation of primary and secondary plastics converting into microplastics.

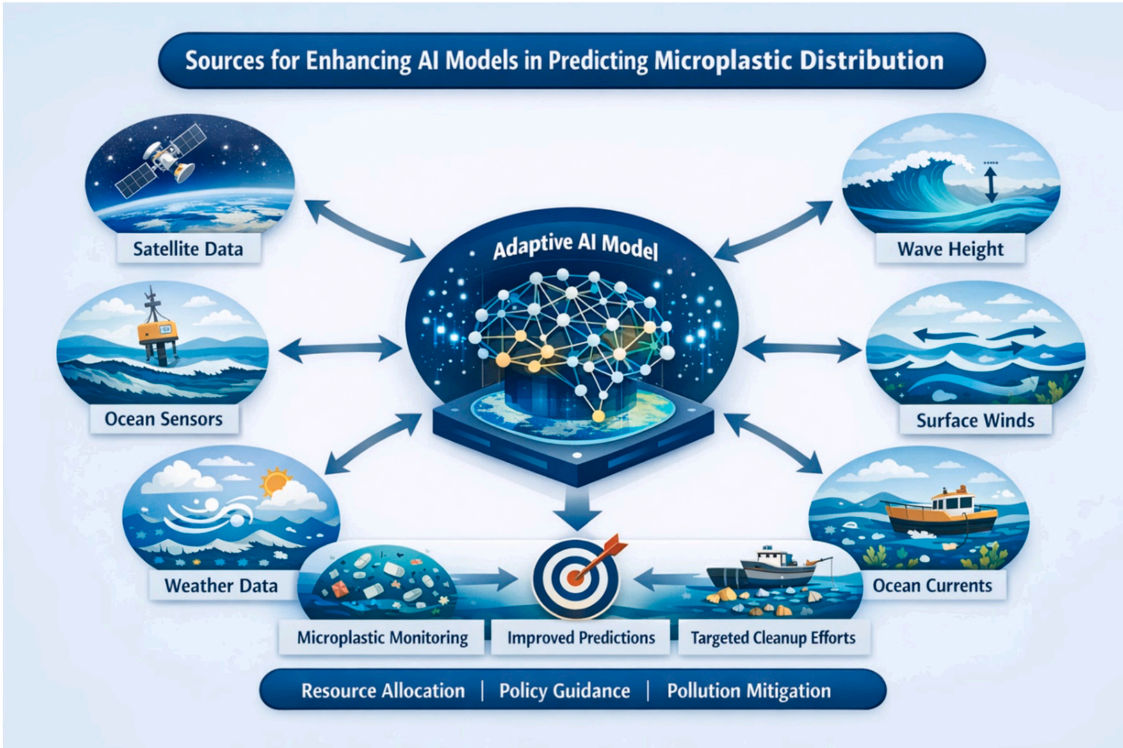

Fig. 3. Machine learning for flow prediction.

environmental models, while useful in simulating physical and chemical oceanic processes, often struggle to predict the complex behaviors and movement of microplastics accurately (Hardesty et al., 2017). This is due to the large number of variables involved, including the diverse types of plastics, varying fragmentation rates, and constantly changing oceanic conditions. AI offers transformative potential for modeling microplastic pollution, but its current application reveals a significant gap between theoretical capability and operational reliability (Zhao et al., 2024). While machine learning (ML) can process complex datasets beyond the scope of traditional models, its effectiveness is contingent upon the quality, quantity, and representativeness of the data used for training. A critical limitation is that many promising models are developed and validated on limited, often geographically biased datasets, raising questions about their accuracy when applied to underrepresented ocean regions. Furthermore, the "black-box" nature of complex deep learning models can obscure the physical reasoning behind predictions, making it difficult for oceanographers to interpret results and integrate them with established hydrodynamic principles. Therefore, while AI can enhance flow prediction, its utility depends on resolving fundamental issues of data equity, model transparency, and integration with physical oceanography.

4.1. *Machine learning for flow prediction*

ML has revolutionized the field of environmental modeling, offering the ability to analyze vast datasets and improve predictive accuracy. When applied to microplastic pollution, ML models are trained on extensive datasets that include oceanic currents, wind patterns, temperature changes, and known plastic accumulation zones. These models can predict the movement of microplastics more accurately than traditional methods by considering multiple, interdependent variables that influence plastic distribution (Phan and Luscombe, 2023). One of the key advantages of ML is its capacity to handle the complexities of ocean dynamics. Deep learning, a subset of ML, is particularly effective in processing and interpreting large and complex datasets that would be overwhelming for traditional models or human researchers (Jia et al., 2021). Through the use of neural networks, deep learning models can identify hidden patterns in the movement of microplastics that may not be immediately obvious. This allows for more accurate predictions of where microplastics are likely to accumulate over time.

Furthermore, AI models can be enhanced by incorporating real-time data from various sources, such as satellite imagery, oceanographic sensors, and remote sensing systems. For example, satellite imagery can provide real-time information on surface-level plastic waste, while oceanographic sensors offer insights into underwater currents and water temperature (Biermann et al., 2020). Fig. 3 gives a pictorial representation of the sources for enhancing the AI models. Integrating these diverse data sources into a dynamic, adaptive AI model enables continuous monitoring of microplastic flows and allows for predictions to be updated as conditions change. Recent studies have demonstrated the potential of AI in predicting microplastic distribution. For instance, neural networks have been used to forecast plastic concentrations based on a range of variables, including surface winds, wave height, and ocean currents (Fetisov and Chubarenko, 2021). These AI models are highly adaptive and improve in accuracy over time as more data is collected, enabling better identification of microplastic hotspots. By enhancing flow prediction, these models can support targeted clean-up operations, allocate resources more efficiently, and guide policy decisions to mitigate future pollution.

4.2. *Comparative analysis of AI methodologies for microplastic research*

While various AI approaches show promise for microplastic modeling and detection, their performance, data requirements, and

Table 3
A comparative overview of key artificial intelligence models applied to marine microplastic detection, modeling, and analysis.

AI Model	Primary Application Context	Typical Datasets Used	Reported Metrics (Range)	Key Limitations / Knowledge Gaps	References
Convolutional Neural Networks (CNNs)	Image recognition from satellite/drone/AUV imagery; microscopic particle classification.	Satellite spectral bands (Sentinel-2, Landsat); lab microscopy images; UAV RGB imagery.	Accuracy: 85–98%; F1-Score: 0.82–0.97; IoU: 0.70–0.90.	Requires large labeled datasets; computationally intensive; "black-box" nature limits interpretability.	Zhou et al., 2025; D, 2025
Recurrent Neural Networks (RNNs/ LSTMs)	Temporal prediction of microplastic transport and accumulation.	Time-series of ocean currents, wind, river discharge, historical pollution data.	RMSE: Varies by scale (e.g., 0.1–5 kg/km^2); R^2: 0.65–0.92.	Struggles with very long sequences; performance drops with sparse or noisy temporal data.	Wongburi and Park, 2023
Support Vector Machines (SVMs)	Classification of polymer types from spectral signatures; binary detection tasks.	Hyperspectral data; FTIR/ Raman spectral vectors.	Accuracy: 78–97.5%; Precision/Recall: 0.75–0.93.	Poor scalability to very large datasets; kernel selection is critical and non-trivial.	Zhu et al., 2019; Shan et al., 2019; Jin et al., 2022
Random Forest / Decision Trees	Feature importance analysis; preliminary flow prediction; risk mapping.	Multi-source geospatial data (land use, proximity to sources, hydrology).	Accuracy: 70–88%; MAE: Varies widely with parameterization.	Can be biased in spatial extrapolation; may not capture complex non-linearities as well as DL models.	Chen et al., 2019
Hybrid Models (e.g., CNN-LSTM, Physics-Informed NN)	Spatio-temporal forecasting; integrating physical laws with data-driven patterns.	Combined remote sensing imagery and oceanographic model outputs.	RMSE: Often 10–30% lower than standalone models.	Increased complexity in training and tuning; lack of standardized architectures.	Krishnamoorthy et al., 2025

suitability vary significantly. The selection of an appropriate model depends on the specific application (e.g., flow prediction vs. pixel-level detection), data availability, and computational resources. The following table (Table 3) provides a critical comparison of prominent AI methodologies employed in recent marine microplastic studies, highlighting their relative strengths, limitations, and contextual performance.

4.3. Model validation and uncertainty in marine contexts

A critical yet often underreported aspect of AI application in marine science is the rigor of model validation. Given the high cost and difficulty of obtaining ground-truth data in oceanic environments, the stated performance of AI models must be scrutinized based on their validation protocols (Kvile et al., 2024). Common approaches include- K-fold Cross-Validation: Used primarily in studies with limited field sample data (e.g., spectral classification of polymers) to mitigate overfitting. However, this often fails to account for spatial or temporal autocorrelation inherent in environmental data. Spatial or Temporal Hold-Out Validation: A more robust method for flow prediction models, where data from a distinct time period or geographic region is withheld for testing. This better simulates operational forecasting but is rarely implemented due to data scarcity. Comparison with In-Situ Measurements: The gold standard, where model outputs (e.g., predicted concentration hotspots) are compared against data from water sampling, plankton tows, or AUV sensors. Discrepancies here are significant, with studies often reporting high pixel-level accuracy for debris detection but poor correlation with quantitative in-situ microplastic mass concentrations. A major limitation is the scale mismatch between satellite pixel resolutions (often >10 m) and the discrete, sparse nature of microplastic samples. Uncertainty Quantification (UQ): It is currently underaddressed in microplastic-specific AI literature. Few studies employ techniques like Monte Carlo dropout, ensemble methods, or Bayesian deep learning to provide confidence intervals for predictions like accumulation zone locations. This lack of UQ severely limits the utility of AI models for high-stakes decision-making in policy or cleanup logistics.

Therefore, while validation metrics reported in controlled studies are promising, their translation to reliable performance in the dynamic, heterogeneous marine environment remains a paramount challenge and a key area for future development.

4.4. Predicting microplastic accumulation zones

One of AI's most promising applications in the field of marine pollution is its ability to predict long-term accumulation zones for microplastics. Accumulation zones, such as ocean gyres, large systems of rotating ocean currents, are areas where plastic debris, including microplastics, tends to concentrate (Van Sebille et al., 2020). Identifying these zones is critical for guiding both clean-up efforts and policy interventions. AI-driven models excel in analyzing ocean dynamics to forecast where microplastics will accumulate over time, allowing for preventive measures to be taken before the pollution reaches critical levels. AI models leverage oceanographic data to predict the formation and movement of gyres and other accumulation points. These models take into account a range of variables, such as current velocity, wind direction, and temperature gradients, which all contribute to the movement of plastic debris. By analyzing these dynamics over long periods, AI can predict the formation of new accumulation zones that may not yet be well-documented or understood by traditional oceanographic methods. This capability allows researchers and environmental organizations to prioritize regions for monitoring and intervention.

For example, combining AI with traditional oceanographic models can help identify lesser-known areas where microplastics accumulate, which may have previously gone unnoticed. AI can also predict how changes in ocean dynamics, such as those caused by climate change, may shift the location and size of accumulation zones over time. By providing these long-term predictions, AI empowers decision-makers to implement preventive measures, such as regulating plastic waste sources, improving waste management practices, or deploying clean-up technologies in strategic locations. Additionally, AI-driven models have the potential to improve the understanding of microplastic "sinks", areas where microplastics settle, such as in deep-sea sediments (Rasta et al., 2021). Identifying these sinks is crucial for assessing the full environmental impact of microplastic pollution, as much of the plastic waste may be invisible at the surface. AI models that integrate data from deep-sea exploration technologies, such as autonomous underwater vehicles (AUVs), can help map out these sinks and estimate the volume of microplastics they contain (Farré, 2020a, 2020b).

By accurately predicting both surface-level accumulation zones and deeper plastic sinks, AI can facilitate more effective and targeted responses to microplastic pollution. This may include the deployment of clean-up technologies like the Ocean Cleanup system, which uses passive collection methods in ocean gyres, or the development of localized waste management policies in regions prone to high levels of plastic pollution. Ultimately, AI's predictive capabilities enable a more proactive approach to managing marine plastic waste, allowing for early interventions that can prevent microplastics from further infiltrating marine ecosystems.

5. Intelligent waste detection systems

The detection and monitoring of microplastic pollution in marine environments present significant challenges due to the particles' small size, vast distribution, and the complexity of the marine ecosystem (Kumar et al., 2023). Traditional methods for detecting microplastics, such as manual water sampling and visual surveys, are labor-intensive, time-consuming, and often cover only small geographic areas (Rani et al., 2023). These limitations hinder the ability to monitor and respond to the growing threat of microplastic pollution on a global scale. AI has the potential to revolutionize the detection of microplastics through the development of intelligent waste detection systems. By automating the detection process, AI can enhance the efficiency and accuracy of microplastic monitoring, allowing for real-time data collection over large areas (Jin et al., 2024). This section explores the use of AI in remote sensing technologies and image recognition systems to detect and quantify microplastics in marine environments.

5.1. AI-powered remote sensing and robotics

Remote sensing technologies, when combined with AI-driven image recognition and data processing algorithms, offer a powerful solution for detecting microplastics across vast areas of the ocean. AI-powered systems can process data collected by satellites, drones, and AUVs to detect plastic waste on the ocean's surface and within the water column (Agarwala, 2023). This approach enables large-scale monitoring that would be otherwise impractical with traditional methods. Satellites and drones equipped with advanced imaging sensors can capture high-resolution images of ocean surfaces, which are then analyzed by AI algorithms to detect plastic debris (Karakuş, 2023). These AI models are trained to recognize the spectral signatures of plastic waste, allowing them to distinguish microplastics from other materials such as organic matter or natural debris. For example, plastic particles reflect light differently than biological materials, and AI algorithms can be trained to detect these unique reflective properties in remote sensing data (Waqas et al., 2023). By automating the analysis of satellite and drone imagery, AI enables continuous and extensive monitoring of microplastic pollution in real time.

In addition to surface-level detection, AI-powered robotics such as AUVs and remotely operated vehicles (ROVs) can be deployed to monitor microplastics at different depths within the ocean. These autonomous systems are equipped with sensors that collect water samples and data on water quality, temperature, and currents. AI algorithms can analyze this data to detect and track microplastic concentrations in the water column. AUVs, in particular, can navigate through different layers of the ocean, providing a more comprehensive picture of microplastic distribution that includes both surface and subsurface environments. One notable advantage of AI-powered remote sensing and robotics is their ability to operate in challenging or inaccessible environments, such as the open ocean or deep-sea regions (Hemanth et al., 2024). These technologies allow for the detection of microplastics in remote areas, where manual sampling is often unfeasible. For instance, AI-equipped drones have been used to survey plastic pollution in the Arctic and Antarctic regions, areas where human presence is limited, but microplastic pollution still poses a threat (Jin et al., 2024). By providing real-time data on microplastic concentrations, these intelligent systems can inform more targeted clean-up efforts and help policymakers make data-driven decisions to mitigate plastic pollution.

5.2. Image recognition and machine vision

AI-driven image recognition and machine vision technologies have emerged as highly effective tools for the identification and quantification of microplastic particles in marine environments (Hu et al., 2024). Traditional methods of detecting microplastics in water samples involve manual counting under a microscope, a labor-intensive process that is prone to human error. AI-based image recognition systems can automate this process, drastically reducing the time and effort required for analysis while improving accuracy and consistency. High-resolution cameras and microscopy systems, when combined with machine learning algorithms, can capture detailed images of water samples and automatically identify microplastic particles based on their size, shape, and color (Massarelli et al., 2021). These systems can be trained to recognize a wide range of microplastic particles, from fibers to fragments, and distinguish them from other particulates such as sand, algae, or organic matter (Hale et al., 2020). This level of precision is crucial for accurately assessing the extent of microplastic pollution, as different types of plastics have varying environmental impacts.

For example, a machine vision system can be used to analyze images of water samples collected from different marine environments. The AI algorithm processes the images, identifying microplastic particles based on pre-programmed criteria, such as particle shape, texture, and reflectivity. Once identified, the system can quantify the number of particles in each sample, providing a detailed assessment of pollution levels. This automated process significantly reduces the time required for microplastic analysis, which is particularly valuable for large-scale studies involving thousands of samples. In addition to detecting microplastics, AI-based image recognition systems can be used to classify different types of plastic particles. Differentiating between various types of plastics, such as polyethylene, polypropylene, or polystyrene, provides valuable information for understanding the sources and behavior of microplastics in the marine environment (Fernández-González et al., 2020). By identifying the types of plastics present, researchers can better track the origins of the pollution and assess which industries or products are contributing most to the problem. This information can then inform regulatory actions or targeted waste management strategies aimed at reducing plastic pollution at the source. The integration of AI into image recognition systems has already demonstrated its potential in various pilot projects and studies. For instance, research conducted in 2021 used AI-based image recognition tools to automatically detect microplastic particles in water samples from coastal areas, achieving a detection accuracy rate of over 90% (Thangagiri and Sivakumar, 2024). Such advancements underscore the potential for AI to streamline microplastic monitoring and enhance the ability to manage marine plastic pollution on a global scale.

5.3. Practical constraints and the scalability challenge

Despite the advanced capabilities of AI-powered remote sensing and image recognition, their practical impact is constrained by several formidable challenges. First, the high capital and operational costs of satellite networks, specialized drones, and AUVs equipped with advanced sensors limit deployment primarily to well-funded research institutions and developed nations, exacerbating global monitoring inequalities. Second, while algorithms achieve high accuracy in controlled studies or with clean imagery, their performance can degrade significantly in real-world conditions such as under cloud cover, in turbulent waters, or amidst organic debris leading to false positives or missed detections. Third, the step from detection to actionable removal remains vast. AI can identify a hotspot, but costly and logistically complex human-led cleanup operations are still required. This highlights a risk of "monitoring without mitigation," where resources are diverted to mapping the problem with increasing precision without corresponding advances in scalable solutions for waste interception and recovery. Consequently, the promise of real-time, global monitoring must be tempered with a realistic assessment of financial barriers, technical reliability in diverse environments, and the critical link between detection and tangible remediation action.

5.4. Integrated AI systems: from data collection to decision-making

While previous sections have examined individual AI components, machine learning models, computer vision systems, and autonomous robotics, the transformative potential of AI for microplastic pollution management lies in integrating these technologies into unified, end-to-end intelligent systems that enable seamless workflows from data collection through analysis, prediction, and actionable decision-making (Guo et al., 2024; Jin et al., 2024).

5.4.1. Architecture of integrated AI monitoring systems

A comprehensive integrated AI system comprises four interconnected layers (Popescu et al., 2024): The sensing and data acquisition layer combines satellite remote sensing platforms (Sentinel-2, Landsat-8), AUVs with multispectral cameras, fixed oceanographic sensors, and drone-based surveillance, transmitting data to cloud-based repositories (Farré, 2020a, 2020b; Hemanth et al., 2024). The data processing and analysis layer employs CNNs for automated microplastic identification achieving >90% accuracy, computer vision systems for image preprocessing, and machine learning algorithms for polymer type identification from spectral signatures (Zhou et al., 2025; Massarelli et al., 2021; Shan et al., 2019). The predictive modeling and decision support layer integrates processed data into hybrid models combining physics-based oceanographic simulations with machine learning to forecast accumulation zones, predict transport pathways, and prioritize intervention locations based on ecological sensitivity and cost-effectiveness (Phan and Luscombe, 2023). The intervention and feedback layer translates insights into operational actions through automated alert systems, optimization algorithms for cleanup deployment, and adaptive management protocols, with intervention outcomes fed back for continuous model refinement (Glaviano et al., 2022).

5.4.2. Practical implementation considerations

Despite their conceptual appeal, integrated AI systems face substantial computational, data, and regulatory constraints (Xu et al., 2021). Deep learning models require GPU clusters costing $500,000–$2 million for training and $50,000–$500,000 annually for operational deployment. Edge computing approaches and model compression techniques (pruning, quantization) can reduce computational requirements by 5–10× while maintaining accuracy, enabling deployment in resource-constrained settings. Training robust CNNs requires datasets of 10,000–100,000 labeled particles across diverse polymer types, with baseline data collection programs costing $1–5 million for regional coverage. Automated quality control algorithms using anomaly detection and active learning approaches optimize data labeling cost-effectiveness (Zhao et al., 2024). AI-driven systems must demonstrate compliance with existing environmental monitoring regulations through validation studies comparing AI outputs with certified reference methods, requiring development of standard operating procedures and potentially updating regulatory frameworks to accommodate algorithmic decision-making (Wu, 2020). International standards for AI monitoring methodologies, analogous to ISO laboratory standards, would facilitate regulatory acceptance and interoperability (Glaviano et al., 2022).

A practical workflow example: Satellites conduct daily coastal surveys with AI algorithms flagging pollution hotspots; alerts trigger drone surveys for confirmation; AUVs are dispatched for subsurface analysis; predictive models forecast dispersion and identify optimal cleanup locations; continuous monitoring assesses effectiveness and updates models. This workflow minimizes unnecessary asset deployments while ensuring rapid response, balancing operational costs with monitoring comprehensiveness (Jin et al., 2024).

5.4.3. Case studies and pilot implementations

Pilot projects demonstrate feasibility. ESA's Sentinel satellites with machine learning algorithms detected Mediterranean plastic accumulations with 85–92% agreement with ship-based observations (Biermann et al., 2020; Topouzelis et al., 2021); Japan's integrated system combining coastal sensors, AI-powered image analysis, and oceanographic models provides real-time Tokyo Bay monitoring with actionable pollution alerts (Tanaka et al., 2022; Tremblay et al., 2023). These implementations, while primarily in well-resourced settings, provide valuable insights into system design and scalable deployment pathways.

6. AI-driven interventions to minimize environmental impact

Beyond its capabilities in detecting and modeling microplastic pollution, AI holds significant promise for driving targeted interventions aimed at reducing the environmental impact of microplastics (Popescu et al., 2024). These interventions can be broad and multifaceted, ranging from informing policy decisions and optimizing waste management to developing new technologies that limit the release of microplastics into marine environments. By leveraging AI's predictive capabilities and its ability to analyze large datasets, more effective and timely solutions can be developed to combat microplastic pollution. This section explores AI-driven interventions in two key areas: policy and decision-making and the design of microplastic-reducing technologies.

6.1. AI in policy and decision-making

Policymakers face considerable challenges when it comes to addressing the global issue of microplastic pollution. The diversity of microplastic sources, the complexity of marine ecosystems, and the difficulty in tracking pollution make it hard to identify which interventions will yield the most effective results (Kurniawan et al., 2024). The integration of AI into environmental policy-making is fraught with complexities that extend beyond technical capability. While AI can generate sophisticated simulations to forecast policy outcomes, its influence is often mediated by political, economic, and social factors. Policymakers may face resistance from industries targeted by AI-informed regulations, or they may lack the technical capacity to interpret and trust model outputs. Furthermore, AI models are only as objective as the data and assumptions built into them; they can inadvertently perpetuate biases, such as favoring mitigation strategies applicable in high-tech contexts over locally appropriate, low-tech solutions in developing regions (Xu et al., 2021). There is also a danger of "paralysis by analysis," where the pursuit of ever-more-perfect predictive models delays the implementation of essential, albeit imperfect, policies. Therefore, the practical impact of AI in policy depends less on algorithmic sophistication and more on building governance frameworks that ensure transparency, foster stakeholder trust, and bridge the gap between data scientists and decision-makers (Popescu et al., 2024). For instance, AI can simulate how different waste management strategies, such as improved recycling systems or bans on single-use plastics, would influence microplastic levels in specific regions or ecosystems. These simulations can account for factors such as population growth, industrial activities, and changing ocean currents, providing a more comprehensive understanding of how these variables interact with plastic pollution.

By analyzing historical data on pollution levels, waste management effectiveness, and environmental conditions, AI models can identify the most significant sources of microplastic pollution. This allows policymakers to target the industries and practices that contribute the most to marine plastic waste, such as textile production, personal care products, and improper disposal of synthetic material (Kibria et al., 2023). Additionally, AI can assist in assessing the effectiveness of plastic reduction initiatives, such as taxes on plastic bags or incentives for biodegradable materials, providing data-driven recommendations for improving these measures. For example, an AI model could be used to simulate the long-term impacts of banning microbeads in personal care products or regulating the release of synthetic fibers from washing machines (Megha et al., 2024). By comparing these simulations with data from real-world case studies, AI can provide policymakers with clear evidence on which interventions are likely to yield the most significant environmental benefits. This level of precision in policy-making could drastically reduce the trial-and-error approach currently used in many environmental regulations. Moreover, AI can help to optimize the logistics of waste management. By analyzing data from municipal recycling systems and waste collection routes, AI can identify inefficiencies and suggest improvements that could reduce the likelihood of plastics reaching the marine environment. In this way, AI supports not only policy development but also the operational aspects of waste management, making it an invaluable tool in the fight against microplastic pollution.

6.2. Integration with international policy frameworks

The effective deployment of AI technologies for microplastic pollution management requires strong alignment with existing international regulatory frameworks and conventions. The International Convention for the Prevention of Pollution from Ships (MARPOL), particularly Annex V which addresses garbage pollution from ships, provides a regulatory foundation that AI-powered monitoring systems can substantially enhance. AI-driven vessel tracking combined with remote sensing technologies can improve compliance monitoring by automatically detecting and documenting potential violations of MARPOL Annex V requirements, including illegal discharge of plastics at sea (Wu, 2020).

United Nations Environment Assembly (UNEA) resolutions, particularly UNEA-5 resolution on marine plastic pollution and microplastics, call for enhanced monitoring, data collection, and scientific cooperation. AI technologies directly support these objectives by enabling systematic, large-scale monitoring of marine microplastic distribution across national boundaries, facilitating data standardization and sharing through common analytical platforms, providing evidence-based inputs for national action plans and policy interventions, and supporting the development of harmonized methodologies for microplastic assessment (Shaik, and S, B., 2025).

Furthermore, AI applications align closely with Sustainable Development Goal 14 (Life Below Water), particularly Target 14.1 which aims to “prevent and significantly reduce marine pollution of all kinds, in particular from land-based activities, including marine debris and nutrient pollution.” AI-powered systems contribute to SDG 14 implementation through several pathways. Enhanced monitoring capabilities provided by AI-driven detection systems offer the comprehensive, continuous monitoring necessary to track progress toward pollution reduction targets (Ghobadi and Sepasgozar, 2025). Predictive analytics for prevention through machine learning models enable proactive identification of pollution sources and pathways, supporting prevention-focused strategies rather than reactive cleanup alone. Evidence-based policy formulation benefits from AI analytics that generate the robust scientific evidence required for effective policy development and regulatory enforcement. Capacity building support can be embedded in AI platforms designed to facilitate knowledge transfer and capacity building, particularly in developing nations with limited traditional monitoring infrastructure.

The integration of AI technologies into these international frameworks requires collaborative governance mechanisms (Outeda, 2024). International standards for AI-driven microplastic monitoring methodologies need to be established to ensure consistency and comparability across nations. Data-sharing platforms should be created that respect national sovereignty while enabling global collaboration, balancing the need for open science with concerns about data ownership and security. Capacity-building programs must be developed to ensure equitable access to AI technologies across all nations, preventing the emergence of a technological divide that mirrors existing economic inequalities. AI development roadmaps should be aligned with international policy timelines and implementation schedules, ensuring that technological progress supports rather than outpaces regulatory frameworks. AI-generated evidence should be incorporated into international reporting mechanisms such as those required under the Basel Convention and regional seas conventions, creating feedback loops between monitoring and policy.

By explicitly linking AI capabilities to these established frameworks, the international community can leverage technological innovation to accelerate progress toward marine pollution reduction goals while ensuring that technological advances serve broader objectives of environmental justice and sustainable development (Usman et al., 2022).

6.3. Designing microplastic-reducing technologies

In addition to informing policy, AI plays a pivotal role in the development of technologies designed to reduce the release of microplastics into the environment. One of the most critical areas where AI can make an impact is in wastewater treatment. Wastewater treatment plants are major sources of microplastic pollution, as they are not fully equipped to filter out the tiny particles that end up being discharged into rivers and oceans. AI can improve the performance of filtration systems by optimizing the design and function of filters to capture even the smallest microplastic particles effectively (Vitali et al., 2023). AI-driven filtration systems can use machine learning algorithms to continuously adapt to the changing composition of wastewater, allowing them to adjust filtration processes in real time. For instance, AI can analyze water quality data to detect spikes in microplastic concentrations and automatically enhance filtration efforts during these periods (Su et al., 2023). These systems can also be used to monitor the performance of filtration materials, predicting when filters need to be replaced or cleaned to maintain optimal efficiency. By reducing the number of microplastics that escape wastewater treatment plants, AI-powered filtration technologies can significantly limit the amount of plastic pollution entering marine environments.

Beyond wastewater treatment, AI can assist in the design of new materials that do not degrade into harmful microplastics. The development of alternative materials is a key strategy in reducing microplastic pollution at its source, as many of the plastics currently in use, such as polyethylene and polypropylene, are prone to fragmentation. AI can be used to analyze the properties of different polymers and identify those that are both durable and biodegradable, allowing manufacturers to produce materials that serve the same functions as traditional plastics without environmental risks (Tran et al., 2024). For example, AI can analyze vast datasets on the chemical composition, mechanical strength, and degradation patterns of various materials. By simulating how these materials break down in different environmental conditions, such as saltwater or sunlight, AI can help scientists design plastics that are less likely to fragment into microplastics. Furthermore, AI can aid in the development of coatings or treatments for existing plastics that prevent them from breaking down into smaller particles. These technologies could have a profound impact on industries that rely heavily on plastics, such as packaging, textiles, and construction. AI is also being leveraged to create materials that break down safely in marine environments. Biodegradable polymers, such as those made from plant-based sources, have the potential to reduce the accumulation of microplastics in oceans, but their development requires careful consideration of both performance and environmental impact (Arif et al., 2024). AI models can evaluate the trade-offs between material durability and biodegradability, guiding researchers in designing products that are both functional and environmentally friendly.

7. Technology readiness levels and implementation challenges

7.1. Technology readiness assessment

Understanding the maturity of AI technologies for microplastic management is crucial for realistic implementation planning. The Technology Readiness Level (TRL) framework, ranging from TRL 1 (basic principles observed) to TRL 9 (actual system proven in operational environment), provides a structured assessment of development status.

High-TRL Technologies at TRL 7–9 are ready for operational deployment. Satellite-based remote sensing with AI image analysis for surface plastic detection operates at TRL 8–9, with multiple operational systems existing, including ESA's Sentinel satellites combined with ML algorithms. These systems have demonstrated reliability in detecting large plastic accumulations, though challenges remain for microplastic-specific identification. AI-powered microplastic identification in laboratory settings has reached TRL 8, with automated microscopy systems using machine learning classification commercially available and widely used in research facilities, achieving greater than 90% accuracy for common polymer types.

Medium-TRL Technologies at TRL 4–6 are in demonstration and validation phases. Autonomous underwater vehicles with AI-powered microplastic sampling operate at TRL 5–6, with several research prototypes tested in controlled marine environments, though technical challenges include power limitations, data processing onboard, and consistent sampling accuracy across varying water conditions. AI-driven flow prediction models also function at TRL 5–6, with multiple models developed and validated against historical data, though operational deployment requires continuous data feeds and regional calibration. Smart filtration systems for wastewater treatment remain at TRL 4–5, with pilot systems showing promise in optimizing filtration efficiency, though scaling to full municipal treatment plants requires substantial infrastructure investment and validation.

Low-TRL Technologies at TRL 2–4 remain in early development. Biodegradable material design using AI operates at TRL 3–4, with research demonstrating proof-of-concept for AI-assisted polymer design, though practical materials meeting cost, performance, and degradation requirements remain in laboratory stages. Integrated AI platforms for policy simulation exist at TRL 2–3, with conceptual frameworks available but validated systems linking environmental, economic, and social factors still requiring extensive development and validation.

7.2. Implementation barriers and resource requirements

The deployment of AI technologies for microplastic management faces several substantial barriers across financial, technical infrastructure, and human capacity dimensions.

Financial barriers present significant challenges to implementation. Initial capital investment for satellite-based monitoring systems requires investments of $50–500 million depending on scope and resolution capabilities, while regional drone-based systems cost $100,000–1 million for equipment, training, and initial operations. Operational costs for continuous monitoring systems incur annual expenses of $5–50 million for data processing, model updating, infrastructure maintenance, and personnel. Research and development for advanced AI algorithm development requires sustained funding typically ranging $1–10 million per application domain, often beyond the capacity of individual research institutions.

Technical infrastructure barriers compound financial constraints. Computational resources for training deep learning models require high-performance computing infrastructure including GPU clusters, representing investments of $500,000–5 million for research-grade facilities. Data infrastructure demands for establishing integrated data collection, storage, and processing systems necessitate cloud computing resources and data management platforms with annual costs of $100,000–2 million depending on data volume. Sensor networks for comprehensive monitoring require deployment of oceanographic sensors, autonomous vehicles, and sampling stations representing investments of $10–100 million for regional coverage.

Human capacity barriers limit implementation even when financial and technical resources are available. Specialized expertise is needed, as AI development and deployment requires interdisciplinary teams including data scientists, marine scientists, engineers, and policy experts. The global shortage of professionals combining AI and environmental science expertise limits deployment speed. Training requirements for operational personnel are extensive, requiring 6–24 months of specialized education in AI system operation, data interpretation, and maintenance. Institutional capacity challenges arise because effective implementation requires institutional frameworks capable of long-term technology management, often absent in resource-constrained settings.

7.3. Disparity between developed and developing nations

The gap in AI technology access and implementation capacity between high-income and low-income countries represents a critical challenge for global microplastic management, manifesting across multiple dimensions.

Resource disparities between nations are stark. Developed nations including those in North America, Western Europe, and parts of Asia possess the financial resources, technical infrastructure, and human capacity to implement advanced AI monitoring systems. Countries like the Netherlands, Norway, United Kingdom, China and Japan have invested substantially in AI-driven marine monitoring platforms (Yan et al., 2024). In contrast, developing nations, particularly Small Island Developing States and Least Developed Countries, face severe resource constraints. Many lack basic oceanographic monitoring infrastructure, let alone advanced AI systems. Annual marine monitoring budgets in some developing nations total less than the cost of a single high-resolution satellite image analysis.

Data availability inequality creates algorithmic bias and limits model applicability. Geographic bias in monitoring means current microplastic data is heavily skewed toward well-monitored regions in Europe, North America, and East Asia, while African coastal waters, Pacific Island nations, and large portions of the Southern Ocean remain undersampled (Cholewińska et al., 2025). This compromises the global applicability of AI models trained on biased datasets. Satellite coverage, while technically global, presents access challenges as high-resolution imagery and processing capabilities remain limited for developing nations due to cost constraints and licensing restrictions.

Technological dependency issues emerge from infrastructure requirements and proprietary systems. Infrastructure dependence means advanced AI systems require reliable internet connectivity, electrical grid stability, and computational infrastructure often unavailable in developing coastal communities most directly affected by marine pollution (Malkova, 2025). Technology transfer barriers arise as proprietary AI algorithms and commercial monitoring platforms create dependency relationships that may not be sustainable or aligned with national priorities.

Capacity building requirements highlight the need for long-term investment. Education gaps reflect the shortage of local experts combining AI, data science, and marine science expertise, which is particularly acute in developing nations and necessitates long-term investment in education infrastructure. Brain drain exacerbates these challenges as trained professionals often migrate to higher-income countries, worsening capacity constraints. Institutional support deficits mean that effective technology deployment requires supporting institutional frameworks including regulatory agencies, research institutions, and enforcement mechanisms that may be under-resourced in developing contexts.

7.4. Strategies for equitable implementation

Addressing these disparities requires coordinated international effort across technology transfer, capacity building, financial support, and data democratization.

Technology transfer mechanisms must be designed for accessibility and appropriateness. Establishing open-access AI platforms and algorithms specifically designed for resource-constrained settings can reduce barriers to entry. Creating regional AI monitoring hubs that provide services to multiple neighboring countries reduces per-country costs through shared infrastructure. Developing "appropriate technology" approaches that adapt AI solutions to available infrastructure ensures that solutions match local capabilities rather than requiring extensive system upgrades.

Capacity building initiatives should foster long-term self-sufficiency. International partnerships linking research institutions in developed and developing nations facilitate knowledge transfer while building local expertise. Fellowship and training programs focused on AI applications in marine science create pipelines of qualified professionals. South-South cooperation facilitating knowledge exchange between developing nations facing similar challenges leverages shared experiences and contextual understanding.

Financial mechanisms must account for differential capabilities. International funding streams specifically designated for AI-driven environmental monitoring in developing countries provide targeted support where it is most needed. Graduated cost-sharing models that account for national economic capacity ensure that implementation costs are proportional to ability to pay. Public-private partnerships leveraging corporate social responsibility commitments can mobilize resources beyond traditional government funding.

Data democratization efforts should ensure equitable access to information. Mandatory data-sharing requirements for satellite operators and commercial monitoring platforms receiving public funding prevent privatization of publicly-funded resources. Creation of global microplastic data commons with standardized, freely accessible datasets enables researchers worldwide to develop and validate models. Investment in ground-truth data collection in under-monitored regions improves global model performance while building local monitoring capacity.

The successful global deployment of AI for microplastic management requires explicit recognition that technological capability alone is insufficient. Equitable access, appropriate technology design, sustained capacity building, and financial support mechanisms must be central to implementation strategies to ensure that AI advances serve global environmental objectives rather than exacerbating existing inequalities (Glaviano et al., 2022).

8. Future directions, critical synthesis, and research agenda

A critical synthesis of the current state reveals that while AI presents significant opportunities, its practical impact on mitigating microplastic pollution is often overstated in the literature. The field is currently characterized by a proliferation of proof-of-concept studies that demonstrate technical feasibility in controlled settings but offer limited evidence of effectiveness at scale or within integrated policy frameworks. The practical impact is not determined by algorithm accuracy alone, but by the successful navigation of the "last mile" challenges: moving from validated models to reliable, maintained, and equitable operational systems.

Future progress hinges on shifting the research agenda from purely normative descriptions of AI's potential to critical, interdisciplinary work that addresses the core implementation barriers: funding sustainable deployment, ensuring equitable access, validating tools in diverse and challenging field conditions, and rigorously measuring downstream environmental outcomes rather than upstream technical metrics. The future research agenda presented here builds upon recommendations from multiple research communities, including calls for enhanced data standardization and sharing protocols (Brander et al., 2020; Su et al., 2023), improved model interpretability and validation frameworks (Zhao et al., 2024; Hu et al., 2024), integration of AI technologies with existing regulatory and policy structures (Wu, 2020; Usman et al., 2022), and explicit attention to equity and capacity-building in global technology deployment (Glaviano et al., 2022; Xu et al., 2021). These challenges, ranging from data availability to the need for global cooperation, require concerted efforts across multiple sectors. This section provides a critical synthesis of current capabilities and limitations, followed by a comprehensive research agenda for advancing AI applications in marine microplastic management.

8.1. Critical synthesis of current state

Current AI approaches for microplastic pollution management demonstrate both significant achievements and persistent limitations requiring realistic assessment.

Strengths include demonstrated capability in automated microplastic identification achieving greater than 90% accuracy in controlled settings, large-scale surface debris detection via satellite imagery, and predictive modeling in well-studied regions. Scalability potential enables continuous monitoring of vast oceanic areas far exceeding traditional methods. Multidisciplinary integration successfully combines oceanographic, meteorological, and remote sensing data. Adaptive learning allows models to improve with additional training data.

Limitations persist across multiple dimensions. Geographic and environmental bias restricts model applicability, as training data from accessible regions limits accuracy in under-sampled ocean areas, deep-sea environments, and diverse ecosystems. Detection remains challenged in complex real-world conditions with interference from organic matter and sediment, despite laboratory success. Model interpretability is limited, as deep learning "black boxes" hinder trust, regulatory acceptance, and scientific understanding. Validation challenges stem from inadequate benchmarking datasets. Substantial implementation gaps separate laboratory demonstrations from operational deployment, with many technologies at low-to-medium TRL facing technical, financial, and institutional scaling barriers. Temporal dynamics create uncertainty, as models relying on historical data may poorly predict future conditions under accelerating climate change.

Furthermore, while the potential of AI is frequently articulated in normative terms, a critical assessment reveals significant hurdles between technical capability and tangible environmental impact. First, there is a prototype-to-product gap: many published models are proof-of-concepts developed on retrospective, curated datasets and fail under operational conditions with real-time, noisy data streams. Second, impact attribution is difficult: even with perfect detection and prediction, reducing ocean plastic load requires effective mobilization of waste management infrastructure, behavioral change, and enforcement—steps where AI provides information but not solutions. Third, there is a risk of techno-solutionism, where investment in advanced monitoring AI could divert resources from fundamental pollution prevention measures, such as improving global waste collection and reducing plastic production. Therefore, the practical impact of AI must be evaluated not by its algorithmic accuracy alone, but by its integration into a broader socio-technical system that enables concrete mitigation actions.

Critical knowledge gaps include poorly understood long-term model performance across temporal scales and shifting environmental conditions. Cross-ecosystem transferability lacks sufficient evidence for generalization across distinct oceanographic regions. Nano-plastic detection below 1 μm remains minimal despite potentially greater environmental risks. Socio-economic integration is weak regarding translation of AI insights into behavior change, policy compliance, and waste management improvements across diverse contexts. Cumulative impact assessment is limited, with models typically addressing single pollutants rather than integrated marine stressors including climate change, acidification, overfishing, and chemical pollution.

8.2. Data availability and quality challenges

One of the most critical challenges facing AI-driven solutions for microplastic pollution is the availability of high-quality, comprehensive datasets. AI models rely on vast amounts of data to accurately predict and detect microplastic flows, accumulation zones, and the effectiveness of interventions. However, the collection of such data in marine environments is inherently challenging. Oceans are vast, dynamic, and difficult to monitor, making the task of collecting consistent and reliable data both logistically complex and expensive.

Currently, data on microplastic pollution is often fragmented and inconsistent, with different research institutions and environmental agencies using varying methodologies for sampling, analysis, and reporting (Brander et al., 2020). This lack of standardization complicates the task of training AI models, as data from different sources may not be directly comparable. Additionally, many regions, particularly in developing countries, lack the resources to conduct comprehensive marine pollution studies, further limiting the availability of data. The geographic concentration of monitoring efforts in well-resourced regions creates systematic biases in available datasets, compromising the generalizability of AI models trained on these data.

To address this challenge, there is a need for more extensive and coordinated efforts to collect marine pollution data. Governments, research institutions, and environmental organizations must collaborate to establish standardized methodologies for sampling and analyzing microplastics, ensuring that data collected from different regions and studies can be integrated and used effectively by AI models. Emerging technologies, such as autonomous drones and underwater sensors, offer promising solutions for collecting real-time data across large oceanic regions (Farré, 2020a, 2020b). The integration of these technologies into coordinated global monitoring efforts could provide the large-scale datasets needed to train AI models and improve their predictive accuracy. International data-sharing agreements and common data standards are essential for creating truly global monitoring capabilities.

8.3. Continuous model updates and adaptation

Another significant challenge is the need for continuous updates and refinements to AI models as new data becomes available and environmental conditions change. Marine environments are constantly evolving, influenced by factors such as climate change, ocean currents, and human activities. As ocean temperatures rise and weather patterns shift, the behavior and distribution of microplastics are likely to change as well. For example, warmer ocean temperatures could accelerate the degradation of larger plastic debris into microplastics, while shifting ocean currents may alter the pathways through which microplastics travel and accumulate (Kakar et al., 2022).

AI models must be regularly updated to account for these dynamic environmental conditions. This requires not only the collection of new data but also the development of algorithms capable of adapting to evolving trends in marine pollution. The integration of climate data into AI models could help researchers predict how changes in the environment will impact the distribution of microplastics over time (Qiu et al., 2023). Continuous learning, a technique in which AI models are designed to update their knowledge base as new information becomes available, will be essential for ensuring that AI solutions remain relevant and effective in the face of shifting oceanic conditions.

In addition to updating models with new environmental data, AI systems must also be refined as more is learned about the sources and behavior of microplastics. Advances in microplastic detection technologies and scientific research will provide new insights into the types of plastics that pose the greatest environmental risks, as well as the pathways through which they enter marine environments. Incorporating these insights into AI models will improve their ability to predict microplastic flows and guide targeted interventions. The development of adaptive algorithms that can incorporate new knowledge without requiring complete retraining represents a critical research priority.

8.4. Global cooperation and standardization needs

Implementing AI-driven solutions to combat microplastic pollution on a global scale requires unprecedented cooperation between governments, industries, and environmental organizations. Microplastic pollution is a transboundary issue, with plastics traveling across international waters, affecting multiple regions and ecosystems. Addressing this global challenge requires coordinated international efforts to establish policies, share data, and implement best practices for reducing plastic waste (Wu, 2020).

One of the most significant barriers to global cooperation is the lack of standardized regulations and policies regarding plastic waste management. While some countries have implemented stringent policies to reduce plastic consumption and improve waste management, others lag behind due to economic constraints or competing environmental priorities. To effectively combat microplastic pollution, there is a need for harmonized international regulations that address the production, use, and disposal of plastics (Usman et al., 2022). AI can play a role in this by providing predictive insights into which policies are most effective in reducing plastic waste and guiding the development of global standards.

Furthermore, the sharing of data across borders is essential for improving AI-driven microplastic mitigation efforts. Currently, many countries and research institutions operate in silos, collecting data independently without sharing it on a global scale. Developing standardized protocols for data collection and sharing will allow AI models to access a more comprehensive dataset, improving their accuracy and applicability in different regions. International collaborations, such as the Global Ocean Observing System (GOOS) and the United Nations Environment Programme (UNEP), could play a pivotal role in coordinating these efforts, fostering data sharing, and promoting the use of AI technologies in marine pollution management. Establishing common technical standards for AI systems, including model validation protocols, performance metrics, and quality assurance procedures, would facilitate comparison across studies and enable more effective knowledge transfer.

8.5. Ethical and socio-economic considerations

The deployment of AI-driven solutions to combat microplastic pollution also raises important ethical and socio-economic considerations. The use of AI technologies in environmental monitoring and policy-making must ensure that the benefits are equitably distributed across all regions, particularly those that are most vulnerable to the impacts of plastic pollution but may lack the resources to invest in advanced technologies. Many developing countries, for example, are disproportionately affected by marine pollution but may not have access to AI-driven tools or data collection technologies.

To address this disparity, international funding and capacity-building initiatives should be developed to support the implementation of AI technologies in regions that are most in need. This could include providing financial assistance for the deployment of autonomous monitoring systems, as well as training local scientists and policymakers in the use of AI tools for environmental management (Glaviano et al., 2022). Ensuring that AI technologies are accessible to a wide range of stakeholders will be critical for achieving a fair and effective global response to microplastic pollution. Beyond financial considerations, ethical frameworks must address data sovereignty, intellectual property rights, and the potential for AI systems to reinforce existing power imbalances between nations.

Additionally, the use of AI in environmental management raises questions about the balance between technological innovation and traditional conservation methods. While AI-driven solutions offer significant advantages in terms of accuracy and scalability, they should be viewed as complementary to, rather than a replacement for, traditional conservation practices such as habitat restoration, community engagement, and policy advocacy. A balanced approach that integrates AI with existing environmental management strategies is likely to yield the most effective and sustainable outcomes. Understanding how AI-driven insights can be translated into behavior change at individual, community, and societal levels remains an important area for research. The socio-cultural factors that influence technology acceptance, trust in AI-generated recommendations, and willingness to implement AI-informed policies vary considerably across different contexts and must be carefully considered in deployment strategies.

8.6. Comprehensive future research agenda

To advance AI applications for microplastic management and address identified gaps, research priorities span seven interconnected areas. These priorities synthesize recommendations from recent systematic analyses of AI in environmental monitoring (Zhao et al., 2024; Su et al., 2023), assessments of technology readiness and implementation barriers (Besiroglu et al., 2024; Kvile et al., 2024), evaluations of policy-science interfaces (Wu, 2020; Outeda, 2024), and frameworks for equitable technology deployment (Glaviano et al., 2022; Xu et al., 2021).

Priority 1: Methodological Advancement; Develop explainable AI approaches for interpretable predictions (Zhao et al., 2024; Xu et al., 2021); hybrid models combining physics-based oceanographic simulations with machine learning (Hardesty et al., 2017; Van Sebille et al., 2020); transfer learning techniques and lightweight algorithms optimized for edge computing (Kvile et al., 2024; Hemanth et al., 2024); extend detection to nano-plastics below 1 μm and improve multi-modal sensing platforms (Zhu et al., 2024; Kumar et al., 2023); integrate climate change projections, vertical transport mechanisms, and probabilistic forecasting with uncertainty quantification (Kakar et al., 2022; Qiu et al., 2023).

Priority 2: Data Infrastructure and Standardization; Establish open-access, internationally governed platforms implementing FAIR principles (Brander et al., 2020; Su et al., 2023); prioritize data collection in under-sampled regions through coordinated campaigns and citizen science with AI-powered quality control (Cholewińska et al., 2025; Padha et al., 2021); develop standardized test datasets, international detection challenges, and consensus reporting protocols (Hu et al., 2024; Rani et al., 2023).

Priority 3: Technology Development; Advance medium-TRL technologies through field demonstrations and public-private partnerships (Kvile et al., 2024); emphasize frugal innovation solutions minimizing infrastructure dependencies, including solar-powered systems and offline-capable platforms (Malkova, 2025; Glaviano et al., 2022); create integration platforms connecting monitoring to waste management optimization with stakeholder visualization tools (Popescu et al., 2024; Jin et al., 2024).

Priority 4: Policy-Science Interface; Establish international standards for AI-driven monitoring methodologies and protocols for incorporating AI evidence into regulatory decision-making (Wu, 2020; Outeda, 2024); conduct rigorous assessments of policy-to-outcome translation, counterfactual analyses, and adaptive management feedback loops (Usman et al., 2022; Kurniawan et al., 2024); perform comprehensive cost-benefit analyses and economic models comparing prevention versus cleanup approaches (Kibria et al., 2023).

Priority 5: Capacity Building and Equitable Access; Establish international training programs combining AI with marine science and develop certification programs (Glaviano et al., 2022; Xu et al., 2021); create regional AI monitoring centers, North-South and South-South partnerships, and governance frameworks balancing data sovereignty with collaboration (Yan et al., 2024; Cholewińska et al., 2025); develop open-source AI platforms with comprehensive documentation and intellectual property frameworks balancing innovation with access (Xu et al., 2021).

Priority 6: Interdisciplinary Integration; Investigate behavioral factors influencing plastic consumption, cultural barriers to technology acceptance, and develop integrated socio-environmental-economic models (Megha et al., 2024; Thacharodi et al., 2024); conduct multi-stressor assessments addressing microplastics alongside climate change, chemical pollution, and habitat loss (Sharma et al., 2023; Arif et al., 2024); link distribution models to ecological assessments, AI-driven health risk assessment, and early warning systems for ecological tipping points (McHale and Sheehan, 2024; Unuofin and Igwaran, 2023).

Priority 7: Long-Term Monitoring and Evaluation; Establish coordinated programs providing temporal trend data and protocols for periodic AI system performance re-assessment (Kvile et al., 2024; Yan et al., 2024); implement adaptive management frameworks incorporating new scientific understanding with feedback mechanisms where deployment experience informs research priorities (Phan and Luscombe, 2023; Zhao et al., 2024).

This agenda recognizes that addressing marine microplastic pollution through AI requires simultaneous advancement across technical, social, economic, and policy dimensions, prioritizing both technological innovation and equitable implementation to ensure AI advances serve global environmental objectives while addressing existing inequalities in capacity and resources.

9. Conclusion

AI presents a powerful tool in the ongoing battle against marine microplastic pollution, offering transformative solutions for the complex and widespread challenges posed by plastic waste. By improving the modeling of microplastic flows and accumulation, AI enables a deeper understanding of how these pollutants move through marine environments, allowing for more accurate predictions of pollution hotspots and accumulation zones. Additionally, intelligent waste detection systems powered by AI provide real-time monitoring capabilities, making it possible to detect and track microplastics more efficiently across vast oceanic regions. These systems, combined with AI-driven interventions, offer a proactive approach to minimizing the environmental impacts of microplastic pollution.

This review has systematically examined the current state of AI applications across three primary domains: (1) predictive modeling of microplastic flows and accumulation, (2) intelligent detection and monitoring systems, and (3) AI-driven intervention technologies. Our analysis reveals significant progress in specific applications, particularly satellite-based surface debris detection and laboratory-based microplastic identification, while highlighting substantial challenges in scaling these technologies for comprehensive, global deployment.

The scientific contribution of this review includes: (1) a systematic classification of AI methodologies based on functional applications and technology readiness levels; (2) explicit linkage between AI capabilities and international policy frameworks including MARPOL Annex V, UNEA resolutions, and SDG 14; (3) critical assessment of geographic and economic disparities in AI technology access and deployment capacity; and (4) a comprehensive research agenda integrating technical advancement with policy implementation, capacity building, and equitable access considerations.

Integrating AI with traditional oceanographic models and harnessing new technologies, such as remote sensing and autonomous robotics, provides a more comprehensive strategy for addressing microplastic pollution. AI can bridge gaps in data, improve detection accuracy, and guide more effective interventions, ultimately helping to preserve marine ecosystems for future generations. However, realizing this potential requires addressing fundamental challenges including data availability and quality, geographic biases in monitoring coverage, the technology readiness gap between promising demonstrations and operational deployment, and particularly the stark disparity in implementation capacity between developed and developing nations.

The pathway forward demands coordinated action across multiple dimensions. Technical advancement must proceed alongside efforts to ensure equitable access, appropriate technology design for resource-constrained settings, sustained capacity building, and robust financial support mechanisms. The integration of AI capabilities with international regulatory frameworks provides a mechanism for translating technological innovation into concrete environmental outcomes aligned with global commitments under SDG 14 and related conventions.

Moving forward, the focus of research and development should be on creating more sophisticated and precise AI models, refining detection technologies, and fostering collaboration between governments, industries, and researchers. Such efforts will be crucial for promoting AI-driven policies and interventions that can effectively combat this growing environmental threat. Future success will be measured not only by technological capability but by the extent to which AI advances translate into measurable reductions in marine microplastic pollution, particularly in the most vulnerable ecosystems and communities. By working together across sectors and ensuring that technological benefits are equitably distributed, the full potential of AI can be realized, significantly reducing the impacts of microplastic pollution and safeguarding the health of our oceans for current and future generations while advancing broader goals of environmental justice and sustainable development.

CRediT authorship contribution statement

David Bamidele Olawade: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Conceptualization. **James O. Ijiwade:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology. **Abimbola O. Ige:** Writing – review & editing, Writing – original draft, Investigation. **Ojima Zechariah Wada:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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