Public Perceptions and AI-Based Monitoring of Microplastics in the United States (2015-2025): A Systematic Review

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Abstract. Microplastics are present in every ecosystem and pose serious environmental and health risks. Public awareness and responses to microplastics have not kept pace with scientific research and detection/distribution. Meanwhile, artificial intelligence (AI) technologies are becoming more common in enhancing environmental monitoring. This systematic literature review examines scientific literature from 2015-2025 to explore public perceptions of microplastic pollution in the United States and assess the usefulness of AI technologies for microplastic monitoring. We conducted a peer-reviewed study search and analysis using the PRISMA methodology. The results show that the public is worried about plastic pollution, but motivations to act relate to cost, trust, and perceived responsibility. AI-based monitoring technologies show great promise for improving detection accuracy and efficiency but remain underutilised in the field. The study identifies a key challenge: closing the gap between technological developments and public awareness and policymaking. The study adopts a social-ecological systems (SES) perspective to highlight the interdependency of environmental, social, and technological aspects. The review ends by pinpointing research uncertainties and the need for stronger interdisciplinary connections to achieve effective environmental governance.

Keywords: microplastics; public perception; environmental behaviour; artificial intelligence; environmental monitoring; machine learning; systematic review; PRISMA; Social-Ecological Systems (SES).

INTRODUCTION

The ubiquity of microplastics in aquatic, terrestrial, and atmospheric environments makes them a major environmental problem. Microplastic particles (those less than five millimetres) come from many sources, such as the breakdown of larger plastic items, synthetic textiles, tyre abrasion, and industrial processes [1, 2]. They are extremely stable and can be transported by water, air, and soil into food chains, raising concerns about ecological and human health effects [3, 4].

Microplastic pollution is not only an environmental problem but also a social and policy issue in the United States. Although scientific knowledge about sources, pathways, and detection techniques has progressed, public awareness and understanding remain uneven [5]. Public perception significantly affects environmental behaviour, policy acceptance, and the effectiveness of mitigation measures [6, 7]. Research indicates that general sentiment about plastic pollution is high, but awareness of microplastics is low, and that behavioural change is linked to cost, trust, and perceived responsibility [7].

Meanwhile, environmental monitoring is changing rapidly due to advances in artificial intelligence (AI). The accuracy and speed of microplastic identification (MPID) have been greatly enhanced through machine learning, computer vision, and automated detection systems [8, 9]. Environmental monitoring and decision-making are areas of great potential, where AI-based approaches can process large amounts of data and ensure more consistent detection. [10]. Yet, although these technologies have advanced, integrating monitoring tools into public awareness and policy initiatives remains limited.

This study will fill this gap by conducting a systematic review of literature published from 2015 to 2025, with a particular focus on the United States. This research aims to analyse public perceptions of microplastic pollution, review AI-based monitoring technologies, and discuss how these monitoring approaches connect to a Social-Ecological Systems (SES) approach [11]. This study aims to do so by offering a holistic perspective on the interplay of environmental, technological, and social aspects in the fight against microplastic pollution.

The following research questions guide the research study:

1) How well is public knowledge of and risk perception of microplastics in the US?

2) What are the social, economic and informational drivers of public attitudes and behavioural reactions to microplastics?

3) How can public perception and AI-based monitoring be aligned in a Social-Ecological Systems (SES) context?

Systematic Review Approach

The study used a systematic review following PRISMA guidelines. The selection of PRISMA was based on its ability to identify, screen, and select relevant studies [12]. This approach supported the organisation, consistency, and replicability of the review, allowing a deeper investigation of sources than a standard literature review. The review focused on peer-reviewed papers from the past ten years (2015-2025). We chose this timeframe because research on microplastics and artificial intelligence for environmental monitoring has grown substantially over the past decade. The review therefore focused on this period to capture the most recent scientific advances and public concerns.

We collected documents from environmental science, public policy, social science, and artificial intelligence. We followed the four phases of the PRISMA process: identification, screening, eligibility, and inclusion (Figure 1) [12]. We used the Scopus, Web of Science, and Google Scholar databases to gather records during the identification phase, and we removed duplicate papers to prevent double counting. In the screening stage, we screened the remaining records by title and abstract to assess relevance.

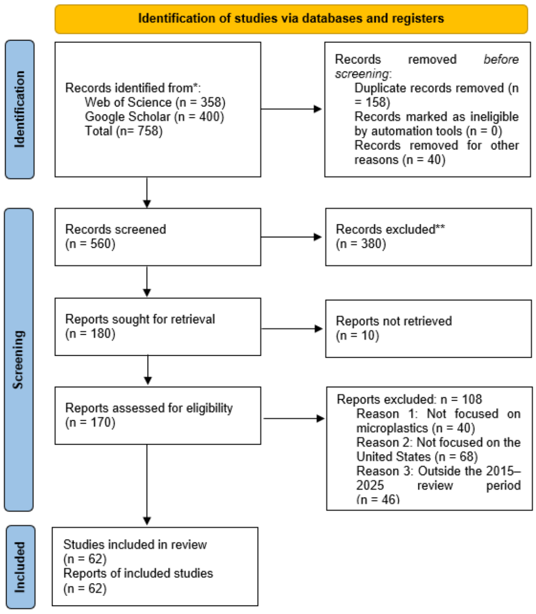

Figure 1 – PRISMA flow diagram of study selection process.

We omitted articles that did not address microplastics, public perception, AI-based monitoring, policy, or US environmental issues. During the eligibility stage, we carefully read the full-text articles to assess their relevance, suitability, and usefulness to the review. Studies that did not pertain to the research objectives and/or yielded no useful information were discarded. These selected studies formed the foundation for the qualitative synthesis, which systematically organised the literature and identified key patterns. We analysed the selected studies using qualitative synthesis [13]. We compared studies to identify themes, debates, and gaps in the literature. Key issues included public awareness of microplastics, risk perception, behavioural responses, traditional monitoring technologies, AI detection technologies, and the relationship between monitoring data and public trust. The researchers considered this approach suitable because the studies came from various disciplines and used a range of methodologies, including surveys, reviews, technical studies, and policy analyses [14]. We also conducted a bibliometric analysis using VOSviewer. The software creates and visualises bibliometric networks, including keyword co-occurrence maps and thematic clusters [15]. VOSviewer mapped relationships between major keywords in the literature, helping identify key research areas associated with microplastic pollution, public perception of microplastics, environmental monitoring, and AI technologies.

The following diagram summarises the process of identification, screening, eligibility and inclusion to select studies for the systematic review. The researchers first identified records through database searches and other sources, then screened them by title and abstract. They evaluated full texts for eligibility and excluded studies that did not meet the inclusion criteria. Finally, they included the remaining publications in the qualitative synthesis.

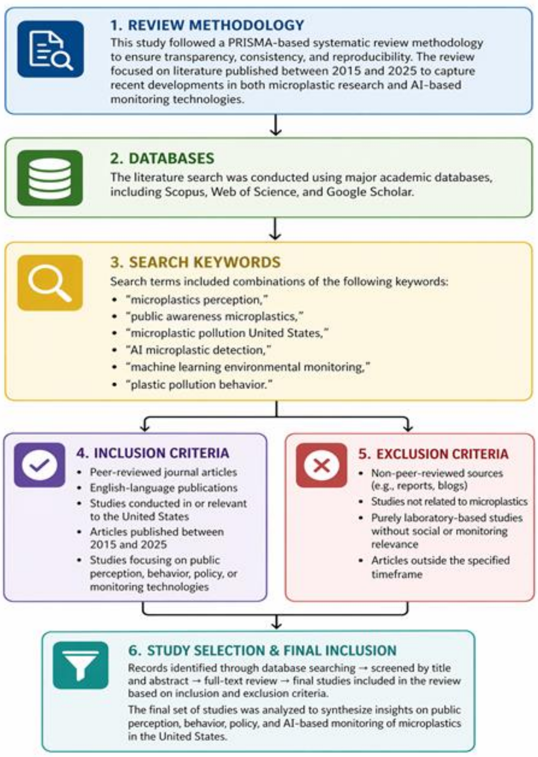

Figure 2 – Flowchart of the systematic review methodology

This figure describes the sequential procedure followed during the study, including the PRISMA-based review approach, database selection, search keywords, and inclusion and exclusion criteria. The flow also shows how the researchers identified the literature, filtered and analysed the relevant studies throughout the process, and selected the final study.

Background and Context: Microplastics in the United States

1) Definition and Classification of Microplastics. Researchers generally define microplastics as plastic particles smaller than 5 mm in their longest dimension. The National Oceanic and Atmospheric Administration (NOAA) [16] uses this definition, but the lower particle-size limit remains a subject of ongoing scientific discussion [17]. Microplastics are particles smaller than 5 mm and are a more analytically complex fraction of plastic pollution than macroplastics; nanoplastics, an emerging field [18, 19], are generally defined as particles less than 1 micrometre (μm) in diameter. Microplastics can also be subdivided by origin: primary and secondary microplastics [20]. This classification matters for source attribution, regulatory targeting, and remediation strategy.

Table 1 – Definition and Classification of Microplastics

Term	Definition
Microplastics	Plastic particles < 5 mm in diameter, encompassing both primary and secondary types [16, 17]
Primary Microplastics	Intentionally manufactured small plastics including microbeads, industrial pellets, and synthetic textile fibres [18]
Secondary Microplastics	Particles resulting from fragmentation of larger plastic items via UV degradation, mechanical abrasion, and chemical weathering [2]
Nanoplastics	A subset of microplastics < 1 μm, detected via advanced spectroscopic methods [19]
Bioaccumulation	Progressive concentration of microplastics in biological tissues through repeated exposure [21]
Monitoring	Systematic collection, analysis, and reporting of microplastic occurrence data to inform regulatory decisions [22]

a) Primary Microplastics. Primary microplastics are manufactured, deliberately being very small, for particular industrial or consumer purposes. Three of these subcategories have been most studied and regulated in the US context. Microbeads are spherical particles of polyethene or polypropylene that are added to personal care products. Microbead-Free Waters Act of 2015 (Public Bill 2472) L. As of July 2017, 114-114 banned the production of rinse-off cosmetics containing plastic microbeads, and as of July 2018 banned sales.

Second, industrial plastic pellets (nurdles) are the feedstock used to manufacture plastics. Transporting and handling pellets can cause spillage and contaminate the environment, and EPA recognises this exposure pathway in its Clean Water Act (33 U.S.C. § 1251–1387) framework for stormwater discharges. Third, textile fibres released from textile products during laundering are a diffuse but quantitatively significant pathway [23].

b) Secondary Microplastics. Secondary microplastics form from physical, chemical, and biological degradation of larger plastic items after they are released into the environment [2]. Common precursor materials include single-use plastic bags, PET bottles, polystyrene foam packaging, agricultural plastic films, and synthetic rubber tyres.

One of the largest secondary sources of microplastics in the United States by volume is tyre wear particles (TWPs). Authors [24] estimated rubber particle generation from passenger and commercial vehicle tyres in the USA at about 800,000 to 1,000,000 metric tons per year. TWPs concentrate polycyclic aromatic hydrocarbons, heavy metals, and the chemical 6PPD-quinone, a transformation product of a tyre antiozonant linked to acute mortality in coho salmon, highlighting the toxicological risks of TWPs from secondary microplastic sources.

2) Sources and Generation Pathways in the World. The USA is one of the world's largest manufacturers and consumers of plastics. In 2022, plastics production in the US rose to over 45 million metric tons, and packaging, construction, automotive, and electronics accounted for over 80% of demand (Plastics Industry Association 2023 [25]). With only 5-6% of plastic waste recycled in the US [22], the US generates excessive plastic waste that breaks down into microplastics.

Top contributors are:

Municipal Solid Waste Systems: Littered packaging and landfill leachate. According to source [22], more than 35 million tons of plastic are produced each year in the US municipal solid waste stream.

Wastewater Treatment Plants: Conventional activated sludge treatment can remove 95-99% of microplastics added to effluent, but the land-based pathway is biosolids applied to agricultural land [26].

Agricultural Sector: Agriculture is another source of microplastics, including plastic mulch films, plastic-coated fertilisers, and irrigation with recycled wastewater [27].

Urban Stormwater Runoff (WSR): Identified as a major source of microplastic inputs to coastal and inland water bodies [28].

Research in the western United States has shown that microplastic particles can deposit in remote wilderness regions, both dry and wet, and have been found far from their sources of origin, indicating that microplastics can be transported long distances in the atmosphere [29, 30].

Marine and Aquatic Activities: Fishing gear, recreational boating, and shipping activities are sources of primary and secondary plastic, such as lost or discarded nets, lines, and buoys [31, 32].

3) Environmental Occurrence and Distribution.

a) Freshwater Systems. The United States has a long history of freshwater environmental surveys. The Great Lakes have been a particular focus of scientific interest [32]. Since then, the US Geological Survey (USGS) and academic partners have found microplastics in nearly all measured inland water bodies. Microplastics are transported through the Mississippi River basin to the Gulf of Mexico [18]. Studies of karst and alluvial aquifers show groundwater contamination [33].

b) Marine and Coastal Environments. The US marine and coastal waters have some of the highest concentrations of microplastics documented worldwide [32]. The North Pacific Subtropical Gyre ('Great Pacific Garbage Patch') collects microplastic pieces and fibres. Beach sediments in California, Florida and the Gulf Coast have concentrations ranging from hundreds to tens of thousands of particles per kilogram [16]. The NOAA Marine Debris Program (2022) coordinates monitoring activities via its Marine Debris Tracker platform, but coastal monitoring lacks national standards.

c) Terrestrial and Atmospheric Environments. Since 2018, studies on terrestrial microplastics have increased significantly. Sewage sludge biosolids are important hotspots in agricultural fields [27]. Deposition rates measured in LA, NYC, and Chicago range from 365 to 1,008 p/m^2/day [29, 30]. Long-range atmospheric transport has been verified in remote wilderness areas of the western US.

d) Human Exposure. Authors [34] estimated that Americans alone ingest between 39,000 and 52,000 microplastic particles from food and water over a year. Subsequent studies have confirmed microplastics in human blood [35], placental tissue [36], and stool [37].

4) The necessity for systematic monitoring. The US monitoring system is extremely diverse. Unlike the Ambient Air Quality monitoring programme under the Clean Air Act [22], the US has no national monitoring framework for microplastics. EPA's existing regulatory program does not include Maximum Contaminant Levels for microplastics under the Safe Drinking Water Act [38] or microplastics under the Clean Water Act. California has taken advanced state-level action with AB 888 (2021), which mandates the State Water Resources Control Board to create monitoring protocols. Longitudinal monitoring data is essential to determine temporal trends and test the effectiveness of source-reduction policies, such as the Microbead-Free Waters Act.

Comprehensive Literature Review: Public Perception and AI-Based Monitoring

1) Overview and Scope. This section provides a synthesis of peer-reviewed and grey literature and survey data related to:

a) Public awareness and risk perception of microplastic pollution in the United States between 2015 and 2025; and

b) The evolution of AI/machine learning tools for microplastic monitoring. Database searches using PRISMA guidelines yielded 62 studies that met the inclusion criteria.

2) Public awareness of microplastic pollution.

a) Trajectory of Public Awareness, 2015–2025. Public knowledge remained limited before 2017. In December 2015, California lawmakers passed a statewide bill prohibiting microbeads, and the media widely covered the legislation. The increase was remarkable between 2019 and 2020, driven by media reporting on microplastics in human stool [37], drinking water [39], and sea salt. The presence of microplastics in human blood also raised concerns and increased public concern [35]. According to Google Trends, the most recent environmental search queries growing in 2024-2025 include the terms 'microplastics in blood' and microplastics health effects' [40].

b) The elements of public information. According to the Yale Program on Climate Change Communication (2022) [41], 71% of all adults in the United States have heard about microplastics. However, only 34% came across information on social media, 29% on television news, and 22% on online news websites. Authors [42], who examined social media discourse, found that health framing is more emotionally resonant than ecological framing. Authors [42], who analysed social media discourse, found that health framing is more emotionally resonant than ecological framing.

c) Demographic Variations in Awareness. Education is the most consistent predictor of awareness [43]. Women are slightly more aware of and concerned about climate change than men [41]. More coastal communities are aware than rural interior communities [41, 43]. Racial/ethnic disparities are under-studied.

3) Risk perception of microplastic pollution.

a) Confucianism, Buddhism, and Hinduism. Media coverage and institutional trust influence public awareness of microplastic pollution. According to authors [42], microplastic health risks are a concern for the general public, with media coverage, notably social media, playing a crucial role in raising the issue. Survey data show that among adults aware of microplastics, 67% are concerned about health risks [43], and that institutional trust has a complex impact on risk perception [41].

b) Empirical findings on risk perception. According to a Pew Research Centre [43] survey, 67% of adults who knew about microplastic pollution in food and water said they were worried about the health risks of these particles. In contrast, 54% said they were worried about risks to wildlife. Risk concern is most closely related to perceived personal exposure [44].

c) Knowledge-Risk Perception-Behavior Gaps. Structural barriers, such as unavoidable routes of exposure (ambient air, public water supplies, and contaminated soils), can foster fatalism and shift responsibility to government actors [45].

d) Environmental Justice Dimensions. Some marginalised communities may be more vulnerable to microplastic exposure, as emerging research suggests [46]. Few environmental justice communities have been surveyed on risk perception.

4) Traditional Monitoring Approaches for Microplastics. Traditional approaches to monitoring microplastics.

a) Sampling Methods. Traditional monitoring involves a multi-step process, including sampling, separation, visual identification, and chemical characterisation [16, 33]. Each step introduces potential error and contamination. Pre-treatment is not standardised [3]. The following section discusses identification and characterisation techniques. Visual identification is common but subjective and has a 20–70% false-positive rate [47]. The dominant chemical methods are FTIR and Raman spectroscopy [48]. Pyrolysis-GC/MS offers bulk quantification, but consumes the sample [3].

b) Identification and Characterisation Methods. Visual identification is common but subjective, with false-positive rates of 20–70% [47]. The most widely used chemical techniques are FTIR and Raman spectroscopy [48]. Pyrolysis-GCMS is used for bulk quantification, but it also destroys the sample [3].

c) Limitations of Traditional Monitoring. Authors [3] found that methodological differences can explain differences of three to four orders of magnitude in reported concentrations. Manual analysis takes 4–8 hours per sample, and analysis costs are estimated at 500–3,000 per sample [16, 22].

Table 2

Criterion	Traditional Methods	AI-Enhanced Methods
Sample Throughput	Low (10–100 particles/hr)	High (1,000–10,000+/hr)
Cost per Sample	High	Lower after investment
Polymer ID Accuracy	Moderate	High (90–98%)
Spatial Coverage	Limited	Expanding
Real-Time Capability	None	Emerging
Standardisation	Partially standardised	Nascent
Data Bias	Operator and method	Training data bias
Regulatory Acceptance	Established	Developing (2022–2025)

5) AI-Based Tools for Microplastic Monitoring.

a) Overview and Development Trajectory. AI applications emerged around 2018–2019 and expanded rapidly, with US institutions among the most prolific contributors [49, 50].

Table 3

AI/ML Approach	Application Area	Key Studies	Performance Highlights
CNN	Image-based detection	[51, 52]	≥95% accuracy
Transfer Learning	Spectroscopic & microscopic analysis	[53]	Reduced training data
Random Forest/ XGBoost	Abundance prediction	[18]	Strong feature ranking
LSTM/ RNN	Temporal modeling	Multiple studies (2022–2024)	Captures seasonal pulses
FTIR + ML	Polymer identification	[48]	90%+ accuracy, 15+ polymers
Hyperspectral + DL	Rapid screening	[54]	1000+ particles/ minute
GAN	Synthetic data augmentation	Emerging (2023–2025)	Addresses class imbalance
NLP	Literature & social media mining	[26]	Topic & sentiment detection

b) Image-Based Deep Learning. Authors [51] reported a CNN-based classifier with 91% accuracy for classifying morphology, compared with non-expert analysts. Transfer learning decreases the amount of training data needed [52]. When combined with FTIR data, ZHU et al. reported polymer-type accuracy of 94–97% using CNNs [53].

c) Spectroscopy-Integrated Machine Learning. Authors [48] developed an automated FTIR pipeline that processes more than 1,000 particles per sample with polymer identification accuracy of 90–98%. Authors [49] have reported that deep learning-based Raman analysis could detect 23% more polymer types and take 85% less time to analyse.

d) Predictive Modelling. Authors [18] created a model predicting microplastic concentrations in 47 US rivers using Random Forest (R^2 = 0.71–

0.84) and found that proximity to WWTPs and urban land cover are important predictors. Researchers have modelled seasonal variability and storm-event pulses with LSTM networks. Physics-informed neural networks are becoming more popular [55, 56].

e) Remote Sensing. Authors [57] created the Floating Debris Index (FDI) and the Plastic Index (PI) of Sentinel-2 imagery. NOAA has adapted prototype detection using satellite imagery into a Marine Debris Monitoring and Assessment Project [16].

f) IoT Sensor Networks. EPA's Office of Research and Development has funded feasibility studies on microplastic sensor networks in Seattle, LA, and Baltimore [22]. The prototype system has reportedly been deployed in the field since 2022 [58].

g) Natural Language Processing. Using NLP-based topic modelling, authors [26] identified 7 main research clusters in 6241 publications. After studying 1,200,000 tweets (2015-2022), authors [40] found that most tweets focused on the environment shifted to health-related framing after 2019.

h) Challenges and Limitations. Limited training data constrains the model's generalizability [51]. Barriers to model interpretability and regulatory acceptance remain [22]. Standardisation and interoperability are key gaps. Environmental justice is rarely discussed.

Theoretical and Conceptual Framework: Connecting Public Perception, AI Monitoring, and SES

1) Social-Ecological Systems (SES) Framework. Microplastics appear in water, soil, air, and food because of human activities such as plastic consumption, clothes washing, tyre abrasion, wastewater disposal, and stormwater runoff [10]. They can affect community health, community support, and public concern, and shape policy support [10, 59]. Authors [60] found that plastic and microplastic pollution are environmental and human health problems in freshwater systems; however, public and stakeholder perceptions may differ. Thus, microplastic pollution should be considered as part of a system involving exposure, public trust, behaviour, monitoring, and policy.

2) Risk Perception and Psychosocial Framework. Risk perception theory explains how people perceive risk in the context of microplastic pollution [60, 61]. According to authors [6], scientific evidence and public perceptions of microplastic risk do not necessarily coincide. Scientists may define risk in terms of exposure, toxicity, and uncertainty. In contrast, the public may define risk in terms of fear, media reporting, personal concern, and the actual risk of harm to health and ecosystems. Authors [62] also noted that public perception of microplastics relies heavily on education, communication, and trust, since microplastics are hard to see directly. Additionally, authors [5] demonstrated that public awareness can shape support for plastic pollution solutions in the US.

3) AI Monitoring Framework. AI-based monitoring provides the technological part of this framework. According to authors [8], AI can improve microplastic detection speed, accuracy, and efficiency. Authors [10] note that AI can aid recovery, image analysis, spectral analysis, classification, and characterisation of microplastics. These tools can be more efficient than traditional manual methods for identifying particle size, shape, number, and polymer type [8]. However, it is not meant to replace well-known techniques like FTIR, Raman spectroscopy, and microscopy. Rather, AI can enhance these approaches by automating manual tasks and enhancing data analysis [9].

4) Synthesis: Connecting Public Perception and AI Monitoring. This review connects public perception and AI monitoring within a single SES framework. AI monitoring can provide scientific data regarding the location, quantity and impact of microplastics in the environment [5, 9]. But this evidence will only support policy action if the public understands and trusts it. According to this framework, the components of AI monitoring are the system's "sensing" function, and public perception is the "response" function [62]. Together, they show that good microplastic governance requires strong monitoring, clear risk communication, public trust, and policy action [63]. AI-based monitoring and scientific evidence create feedback loops with public perception and policy support, which in turn affect risk reduction, environmental exposure, and microplastic sources.

This framework supports the review's main argument: technological innovation and social understanding of microplastic pollution in the United States should be considered [8, 10]. In this unit, students will engage in the critical process of synthesising and discussing scientific knowledge and concepts in relation to public trust and monitoring.

1) Main Findings. Authors [9, 64] showed that AI-camera systems can detect microplastics in real time, and authors [65] reported that artificial intelligence reduces the time and labour involved in traditional monitoring. Combined with advanced spectroscopy (FTIR, Raman) and hyperspectral imaging, deep learning architectures such as Convolutional Neural Networks (CNNs), U-Net, and YOLO consistently deliver detection accuracy rates above 90%. AI-assisted tools can enhance microplastic collection, image processing and classification, and characterisation [10]. Authors [9] also proposed that AI could enhance existing microplastic analysis tools and support the development of future generative AI applications.

Meanwhile, public awareness has not progressed as quickly as monitoring technology. The authors of [6] found a gap between scientific evidence and people's perceptions of microplastic risks. Risk is typically expressed as a combination of exposure, toxicity, and uncertainty, whereas the public often reacts based on concerns, media coverage, and perceived harm [62]. Public perception about plastic pollution can affect support for solutions in the United States [5]. Figures 3 & 4 supported the review by illustrating the interconnections across the literature.

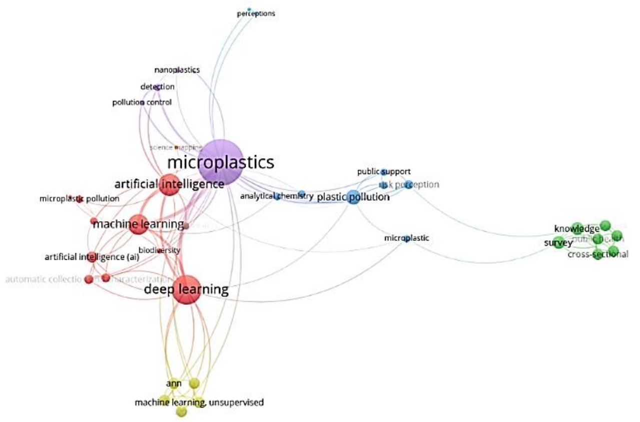

Figure 3 – The co-occurrence map of public perception and AI-based microplastic monitoring studies created using keywords in VOSviewer

For instance, it highlighted the link between perception studies and AI-based monitoring studies in the public sphere, as well as the development of these two types of studies as separate research fields [15].

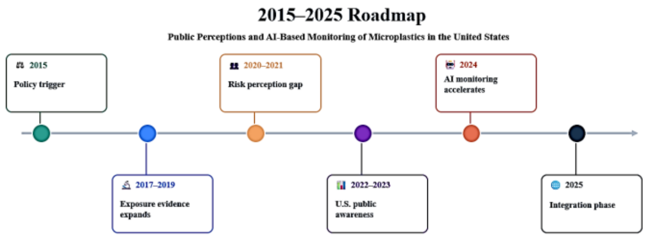

Figure 4 – Microplastic US public perception and AI-based monitoring roadmap, 2015-2025

The map shows major research themes in microplastics, AI, machine learning, public perception, risk perception, public health, and environmental monitoring. Node size indicates keyword occurrence, and links indicate relationships between keywords.

2) Strengths and Limitations. According to authors [8], AI technologies can improve microplastic detection speed, efficiency, and data processing. Authors [56] further showed that machine learning can support faster, more accurate microplastic counting. These strengths provide timely, efficient, and standardised monitoring, which is crucial because traditional methods are often slow, labour-intensive, and hard to standardise [8, 56].

AI models, however, still have limitations, particularly when they are trained on clean laboratory data and then applied to more complex environmental samples [66]. Real samples can contain sediment, organic matter, weathered plastics, and mixed particles. In addition, authors [67] found that past public perception studies also have methodological drawbacks, such as inadequate sampling techniques and questionnaires.

3) Research Gaps. Authors [56] found that a major challenge for accurate AI-driven microplastic monitoring is the lack of publicly available image and spectral datasets. AI models cannot be consistent without standardised datasets.

Another major gap is the lack of linkage between AI monitoring and public perception research. AI research more often focuses on detection accuracy, while social science studies focus on awareness, concern, and behaviour. Few studies examine the link between AI technology-produced monitoring data and public trust, risk perceptions, and policy support [56, 68].

4) Connecting Public Concern and Monitoring. Uncertainty in microplastics science poses challenges for risk communication [6]. But when scientists communicate what they know and what they don't understand, they can foster trust. As authors [62] note, the public must understand the significance of microplastics because, unlike other plastics, they are not visible in everyday life.

Authors [69] found that deep-learning-based image processing can quickly and cheaply identify microplastics in consumer products. This kind of instrument may help make invisible pollution visible to the general public. Communicating AI-generated data effectively can support public understanding, stronger policy responses, and improved environmental governance.

Implications for SES, Resilience, Vulnerability, Disasters, and AI Monitoring

1) Socioeconomic Vulnerability and Environmental Justice. Exposure to and risk from microplastics are not uniform across populations and are shaped by infrastructure quality, geographic location, and socioeconomic status (SES). The increased risk of disproportionate exposure in lower-SES communities stems from their proximity to urban runoff systems, industrial areas, and/or ageing water systems, which are sources of higher microplastic contamination [3, 4]. Limited institutional capacity in environmental monitoring and lower access to quality water treatment technologies exacerbate these inequalities.

How people perceive risk also matters and shapes awareness, trust, and responses to new contaminants, which SES also influences. Institutional trust is lower in some communities, and they may lack the means to respond effectively [70, 71]. This creates a vicious cycle: more vulnerable individuals are more exposed and less able to adapt. Thus, microplastic pollution is not only an environmental problem but also an environmental justice problem, requiring targeted interventions to address inequalities in exposure and access to information.

2) Resilience in Social-Ecological Systems (SES). Resilience is a social-ecological system's ability to endure shocks and changes while continuing to function [72]. Unlike other environmental stressors, microplastics are difficult to detect and address because of their persistence, pervasiveness, and low visibility, posing an additional challenge to SES resilience. However, microplastics are not an acute contaminant: they are a chronic, diffuse stressor and therefore hard to manage with conventional regulatory measures. Measures of adaptive capacity include systems with strong monitoring structures, strong governance, and high levels of public trust. However, systems that lack these attributes are more susceptible to long-term deterioration. Advanced monitoring technologies, including AI systems, can further improve resilience by enabling early detection and prediction. But the usefulness of these tools depends directly on their availability, transparency, and incorporation into governance processes.

3) Disasters and Microplastic Mobilisation. Flooding, hurricanes, and wildfires are some environmental disasters that play an important role in redistribution and microplastic movement. Heavy rain, flooding, and extreme precipitation events can resuspend contaminated sediments, carry urban debris, and overload wastewater treatment plants, resulting in high levels of microplastics in surface waters [23, 73]. Likewise, wildfires are a source of secondary microplastics: when plastics burn, the resulting Secondary Microplastics can be deposited in the atmosphere. These processes convert microplastics from a chronic environmental issue into an acute exposure risk during disaster events. Because of climate change, such events are becoming more frequent and intense, worsening the issue. For this reason, microplastic monitoring and mitigation need to be integrated into disaster preparedness and response strategies to tackle these "stormy" peaks of microplastic contamination.

4) AI Monitoring as a Decision-Support Tool. AI and machine learning (ML) technologies are becoming powerful tools for improving environmental monitoring and decision-making. AI-driven solutions facilitate the integration of diverse and vast datasets, such as those from remote sensing, on-site measurements, and laboratory analysis, which helps identify contamination trends and forecast microplastic movement [74]. They can greatly enhance the efficiency and spatial resolution of monitoring efforts. However, AI monitoring systems face challenges. Data limitations, including spatial bias and non-standard datasets, can cause inaccuracies and limit generalizability. In addition, the lack of transparency in some machine learning models could erode public trust. Importantly, AI technologies are often unevenly available, and there is concern that they may exacerbate current SES inequalities. AI should therefore be treated as a socio-technical tool, not just a technical one, and addressed alongside other governance and equity issues.

Future Research and Policy Recommendations

1) Standardisation of monitoring protocols. One of the biggest challenges in current microplastic studies is the lack of standard sampling, processing, and analysis methodologies. Different definitions of particle size, sampling procedures, and reporting units make it difficult to compare results across studies, and regulatory guidance on particle size remains lacking [3]. Future research should place greater importance on standardising protocols for monitoring microplastics in environmental media (water, sediment, air). Centralised, national databases would help to share and synthesise data further.

2) Advancing AI Datasets and Models. High-quality, representative datasets are essential to the effectiveness of AI-based monitoring systems. Existing datasets often cover only spatial and temporal extent and can be skewed toward areas with high resource density. Future work should focus on creating open-access, standardised datasets that incorporate multiple data sources, such as remote sensing, laboratory measurements, and citizen science contributions. Furthermore, it is crucial to validate models and ensure transparency to guarantee reliability and trust in AI-generated insights.

3) Public Education and Risk Communication. Risks are often low-visibility and low-perceived, and effective risk communication is critical to addressing them. Public education efforts should raise awareness without fear-mongering or false information. Studies suggest that trust in information sources strongly shapes risk perception and behavioural responses [71]. Therefore, communication must be clear, transparent, and community-engaged. Messages tailored to regional conditions and SES can further improve effectiveness.

4) Citizen Science Integration. Citizen science offers a new and exciting way to augment monitoring efforts and engage the public. Community-based sampling programs can provide high-quality data and build awareness and trust in scientific processes. New developments in low-cost sensors and mobile technologies have also made it easier for the public to be involved in environmental monitoring [75]. But data quality and standardisation issues require resolution through training, validation procedures, and links to professional monitoring systems.

5) Policy and Governance Actions. However, in the United States, regulations remain limited, and despite evidence of microplastic contamination and possible health effects, the laws are still in infancy. Federal requirements for microplastics in drinking water and environmental media do not currently exist. Policymakers should include microplastics in ongoing water quality policy and establish guidelines to monitor and mitigate microplastics. Collaborative inter-agency efforts, such as between environmental, public health and technological agencies, will be vital to good governance. In addition, policies should include an equity dimension to avoid harming vulnerable groups.

CONCLUSIONS

The data presented in this systematic review show that microplastic contamination is not only an environmental problem, but also a social-ecological and technological problem in the United States. Scientific advances, particularly the development of AI-based detection and monitoring, have enhanced the capacity to detect, quantify, and model microplastic pollution. However, these technologies remain only loosely linked to public perceptions, risk communication, and policymaking. The review also briefly notes a lack of scientific evidence and a science-public gap. Despite public concern, gaps in knowledge, media influence, and communication result in varying behavioural responses to microplastics. While AI monitoring offers benefits in detection, scalability, and prediction, it also faces significant hurdles, including the need for data standardisation, real-world application challenges, transparency, and regulatory acceptance. A social-ecological systems view suggests that feedback among environmental exposure, awareness, monitoring, and governance is a fundamental driver of microplastic pollution. Future progress requires greater integration of AI monitoring, social science, public engagement, and policy action. An integrated, multi-sectoral strategy is required to build public trust, improve environmental decision-making, and strengthen long-term environmental and public health resilience.

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