Emerging AI Solutions for Hazardous PET Waste in Marine Environments: A Review of Underexplored Paradigms

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Emerging AI Solutions for Hazardous PET Waste in Marine Environments: A Review of Underexplored Paradigms

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Abstract

Polyethylene terephthalate (PET) pollution, due to its persistence, chemical recalcitrance, and widespread usage, represents a growing hazard to marine ecosystems. Its accumulation contributes to long-term ecotoxicological risks, food chain contamination, and environmental degradation. Addressing this challenge necessitates the adoption of scalable, efficient, and intelligent strategies for monitoring, collection, and degradation. While artificial intelligence (AI) has shown promise—particularly through machine learning (ML), deep learning (DL), and computer vision (CV)—these approaches have already been extensively covered in recent reviews and are therefore beyond the scope of this research.

Instead, this article focuses on underexplored and emerging AI technologies with untapped potential in marine PET management. These include reinforcement learning, generative AI, Edge AI, soft robotics, federated learning, explainable AI, decision support systems, and large multimodal models (LMMs). These technologies offer new capabilities for real-time decision-making, distributed data processing, autonomous biodegradation, and intelligent system design—critical tools in managing hazardous waste scenarios—yet remain largely absent from current PET-focused research.
We synthesize existing literature where applicable—such as in reinforcement learning, Edge AI, and soft robotics—while also investigating areas where research is still sparse or speculative, such as federated learning and LMMs. This addresses the need for a comprehensive review that not only maps current applications but also identifies conceptual gaps where emerging AI technologies can drive future innovation.
Through a bibliometric analysis of leading scientific databases and a thematic synthesis of technological trajectories, this article straddles the line between a traditional review and a forward-looking conceptual overview. It aims to inform researchers, inspire interdisciplinary collaboration, and advance sustainable, hazard-mitigating solutions for marine PET management in a rapidly evolving technological landscape.

Keywords: plastic, marine, pollution, polyethylene terephthalate, hazardous waste, ecotoxicology, environmental risk, enzymatic biodegradation, microbial depolymerization, bioremediation, waste management, artificial intelligence, deep learning, reinforcement learning, Edge AI, soft robotics, generative AI, large language models, decision support systems, detection, classification, modeling, prediction

1 Introduction

The ocean has long acted as a sink for pollutants, but rising levels of marine pollution now pose a global environmental challenge. Central to the United Nations' Sustainable Development Goals (SDGs), particularly SDG 14, is the reduction of marine pollution (Willis et al, 2022). A growing concern among researchers and stakeholders is the accumulation of non-biodegradable waste, especially plastics (Ahmed et al, 2018). From 1950 to 2018, around 8.3 billion metric tons of plastic were produced, with output projected to quadruple by 2035 and reach 1,600 megatons annually by 2050. Since 2020, over 400 megatons of plastic waste have been generated each year (Ali et al, 2021). Plastic pollution has become a dominant form of marine debris, found even in remote areas like polar regions and the ocean floor, severely impacting marine and introducing hazardous, persistent contaminants into food webs (Löhr et al, 2017); (Oosterhuis et al, 2014).

Based on size, plastic waste is globally categorized into three primary types: macroplastics ($> 25\ mm$), mesoplastics (5–25 mm), and microplastics (1–1000 um). These types pose significant global economic and environmental hazards to coastal and marine ecosystems (Karthik et al, 2018), including chemical leaching, toxic additives, and sharp-fragment injuries to organisms. In 2022, global plastic production reached

400.3 MT. Of this total, 90.5% consisted of polymers derived from fossil fuels, while 0.6% originated from biological sources (Europe, 2022). Global estimates indicate that between 4.8 and 12.7 megatons of plastic enter the ocean annually (Jambeck et al, 2015). Plastic packaging accounts for 40%, consumer goods for 12%, and textiles for 11%, together comprising more than two-thirds of all plastic waste. Ultimately, only 9% was recycled and the remaining 28% was either released into the environment or disposed of in unregulated landfills or open fires where they generate hazardous byproducts, such as dioxins and polycyclic aromatic hydrocarbons (Plastics, 2022) . Consequently, marine litter is a prevalent issue in 75% of coastal areas, while the remaining areas were classified as 'non-problem areas' (Zheng et al, 2005; Sivan, 2011; Ali et al, 2021). Inadequate recycling processes increase plastic waste in various habitats and play a significant role in the proliferation of microplastics resulting from plastics breakdown.

Microplastics are plastic particles under 5 mm in size, originating from the breakdown of larger plastics. They can degrade into even smaller nano-plastics and accumulate in deep-sea sediments. Smaller fragments tend to sink faster, aiding biofilm formation (Adam et al, 2020). Microplastics pose serious hazards to aquatic ecosystems and biodiversity, as they are easily ingested and bioaccumulated by marine organisms. This contamination can transfer to humans through seafood consumption, potentially causing toxicological effects such as endocrine disruption, oxidative stress, and genotoxicity.

Recycling and mechanical sorting have increasingly become the preferred methods for reusing plastic waste. However, repeated recycling cycles can significantly degrade the physical and chemical properties of most plastic materials, ultimately limiting the commercial viability of the resulting polymers. Chemical recycling offers the potential to recover polymers and other valuable compounds from plastic waste, but its effectiveness depends on the catalysts used and the feasibility of tailored methods (Ali et al, 2021). These chemical processes also raise hazardous concerns due to the release of corrosive reagents and secondary toxic pollutants. Figure 1 shows a comparison of the different organic structures of various types of synthetic plastics.

Understanding the different categories of synthetic plastic polymers is essential, as their structural characteristics affect their recyclability and the advantages of their recycling techniques. Synthetic plastic polymers can be categorized into two groups: carbon-carbon (C-C) and carbon-oxygen (C-O) polymers. C-C polymers, which include polyvinyl chloride (PVC), polypropylene (PP), polyethylene (PE), and polystyrene (PS), account for 77% of the global market; and typically degrade through thermal or photo-oxidation processes. In contrast, C-O polymers, including polyurethane (PU) and polyethylene terephthalate (PET), represent a significant market share of over 18%. Polyethylene terephthalate (PET) is a semi-crystalline, polymeric polyester characterized by its high strength, transparency, and safety properties but also by its hazardous persistence and resistance to natural degradation.

The widespread use of PET has led to the development of numerous treatment methods, some of which are illustrated in Fig. 2. Similarly, the gradual accumulation of PET in the environment has fostered a unique ecosystem that supports the evolution of microorganisms capable of degrading PET polymers and utilizing their

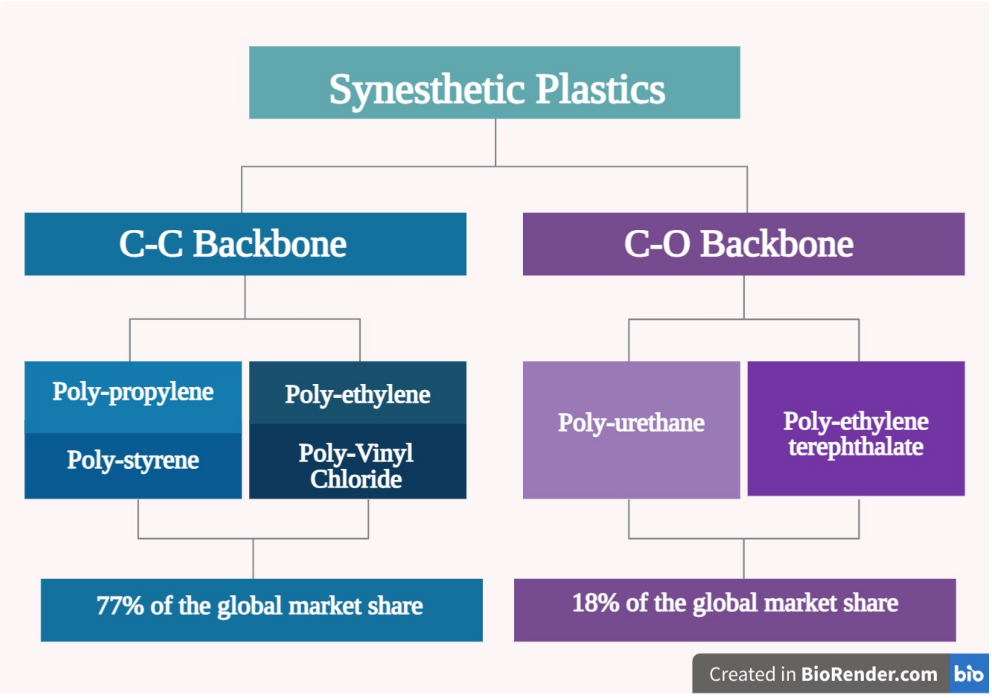

Fig. 1 A comparison of the different organic structures of various types of synthetic plastics.

monomers for cellular growth. Although PET has traditionally been considered stable and non-biodegradable, recent discoveries and extensive research on PET-degrading microorganisms and enzymes have opened new avenues for addressing PET accumulation (Gambarini et al, 2021; Gao et al, 2022; Kawai et al, 2019; Perrin et al, 2020; Qi et al, 2021).

Microorganisms are well-known biological agents capable of degrading complex molecules into smaller, simpler ones, a process referred to as microbial degradation. They play a vital role in maintaining ecological equilibrium by facilitating numerous biochemical processes (Reineke and Schlömann, 2023). Fungi, bacteria, and actinomycetes can degrade organic compounds or polymers during aerobic or anaerobic degradation, resulting in simpler substances such as carbon dioxide, water, methane, and other inorganic compounds, which they subsequently utilize as nutritional sources (Gao et al, 2022). Microorganisms can facilitate the degradation of high molecular weight polymers through enzyme production, such as PET, into valuable chemicals (Kushwaha et al, 2023). The degradation of PET occurs via the depolymerization of these long chains, yielding terephthalic acid (TPA), ethylene glycol, and the monomers mono(2-hydroxyethyl) terephthalate (MHET) and bis(2-hydroxyethyl) terephthalate (BHET) (Qiu et al, 2023). Despite the availability of chemical methods for PET degradation, these approaches are often undesirable due to their high costs and the generation of secondary pollutants and the hazardous release of toxic intermediates.

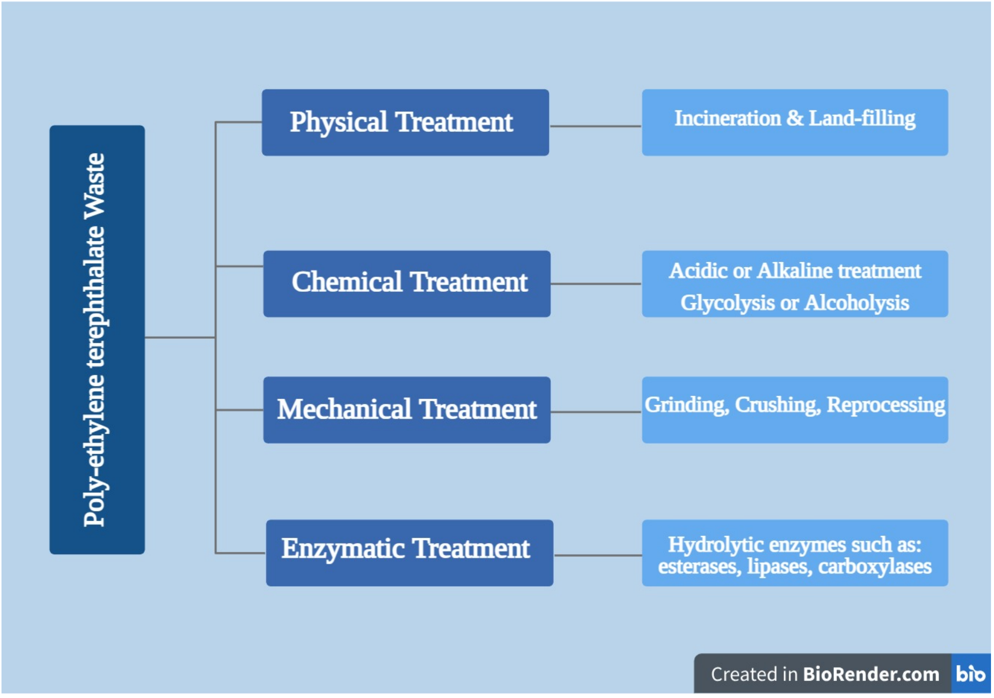

Fig. 2 Different PET treatment methods and some examples for each

In contrast, biodegradation, utilizing microbial isolates is considered cost-effective and environmentally friendly, such as PETase, MHETase, lipases, cutinases, esterases, and carboxylesterases (Qiu et al, 2023). Biodegradation has benefited tremendously from artificial intelligence (AI).

The evolution of AI technologies has provided various systems with advanced learning and decision-making abilities. This has resulted in improved efficiency and sustainability in several sectors (Kamishima et al, 2018); PET management is one of them. For example, predictive modeling, that benefits significantly from the potential of AI techniques, is of a central importance for enzyme functions optimization (Baskerville et al, 2019; Manikandan et al, 2023). Another example is robotics–a subfield of AI–has been employed for plastic waste manipulation and segregation, demonstrating better abilities to work faster and longer than humans.

This review addresses the various applications of AI in plastic waste and environmental engineering, with a particular focus on PET in aquatic ecosystems. We are especially intrigued by the current dominance of certain AI approaches in PET management—namely, machine learning, deep learning, and computer vision—contrasted with the near-complete absence of others that may hold comparable or even greater potential. Rather than offering a comprehensive survey that would significantly overlap with existing literature, we adopt a selective approach focused on underexplored AI subfields. Specifically, we examine reinforcement learning (RL), generative AI

(GenAI), edge AI, soft robotics (SR), federated learning (FL), explainable AI (XAI), decision support systems (DSS), and large multimodal models (LMMs)—areas that have received limited attention despite their promise in advancing marine PET management. Our review pursues a two-fold objective: first, to highlight the preliminary research efforts within these emerging AI areas as they relate to PET management; and second, to draw the attention of the research community to additional, relevant applications—both within these underexplored areas and in entirely neglected AI domains. Figure 3 illustrates the structure of the proposed overview, outlining the main sections and subsections corresponding to AI subfields in PET management. The contributions of this overview can be summarized as follows:

1. This overview highlights the limited representation of various AI technologies in marine PET management and encourages a broader perspective by identifying research topics that could benefit from underexplored AI techniques. We support this rationale through analysis of term co-occurrence networks using VOSviewer, applied on search results from Web of Science and Scopus, in addition to analysis of recent reviews. For transparency and reproducibility, we provide the search queries used in our analysis.
2. Our review delves into the emerging role of reinforcement learning (RL) in PET management, highlighting its use in optimizing drone navigation, dynamic marine interception, and multi-agent cleanup strategies. RL-based models are also explored as frameworks for enhancing biodegradation, informing adaptive policy design.
3. We present a diverse range of Edge AI applications in PET management, including marine debris detection, tracking, autonomous collection, and classification. The discussion extends to AI-enhanced cleanup operations, real-time waste sorting and recycling, and contamination prevention.
4. We explore the transformative potential of soft robotics for marine PET management, including their role in collecting plastic waste from complex aquatic terrains and deploying enzyme carriers for targeted biodegradation. This field opens avenues for scalable, autonomous, and biologically-integrated cleanup technologies.
5. We discuss the underexplored value of federated learning in facilitating collaborative marine pollution modeling across distributed research entities and coastal monitoring stations, while preserving data privacy. Its application in multi-source model training for PET detection and biodegradation prediction is examined as a privacy-preserving alternative to centralized data collection.
6. We emphasize the potential of decision support systems (DSS) in integrating heterogeneous data sources—ranging from sensor networks to satellite imagery—to inform real-time interventions and long-term strategic planning in PET management. Specific use cases include waste accumulation forecasting, site prioritization for intervention, and evaluating policy trade-offs.
7. The review examines the growing utility of generative AI (GenAI), particularly in addressing the data scarcity challenge pervasive in PET-related tasks. We discuss how synthetic data generation can support model training for detection and tracking, and how GenAI can simulate hydrodynamic scenarios such as aquatic current patterns to assist predictive modeling.

8. We examine the emerging role of large language models (LLMs) and large multimodal models (LMMs) in marine PET management. These models offer promising capabilities in synthesizing scientific evidence, environmental reports, and stakeholder communications, as well as in generating domain-specific insights and predictive scenarios. We highlight their potential to bridge textual and visual data sources—such as satellite imagery and annotated maps—thereby enhancing situational awareness, automated reporting, and community engagement. We also discuss current limitations related to domain adaptation, resource intensity, and output reliability, framing this section as a forward-looking agenda for integrating LLMs and LMMs into future PET research and policy support systems.
9. We highlight the role of explainable AI in enhancing transparency and trust in AI-powered PET management systems. The review discusses how interpretable models can assist stakeholders in understanding AI decisions, particularly in regulatory, ecological, and policy-sensitive contexts such as enforcement strategies and biodegradation safety assessments.
10. Our review provides a categorized overview of the datasets available across these AI applications in PET management, including those for waste detection, PET biodegradation, RL model training, edge-device deployment, and multimodal DSS inputs.
11. Finally, we offer insights into the synergies among these AI technologies and how their integration can enable more holistic and adaptive PET management strategies. We conclude by discussing key challenges and future directions, including promising but nascent paradigms such as neuromorphic computing and self-organizing intelligent agents.

The contributions listed above are meant to address the following research questions:

1. Which areas of marine PET management remain unaddressed by current AI research, and which AI paradigms offer the most promising, yet unexplored, solutions for these gaps?
2. To what extent can underexplored AI technologies—such as reinforcement learning, generative AI, edge AI, soft robotics, federated learning, decision support systems, explainable AI, and large multimodal models—advance marine PET waste management beyond the capabilities of traditional machine learning, deep learning, and computer vision approaches?
3. How could the adoption of underexplored AI paradigms in marine PET management influence environmental monitoring outcomes, policy decisions, or conservation strategies on a global scale?

The structure of this article is as follows. Section 2 establishes the theoretical and conceptual foundation, introducing key terminologies and framing the scope of the proposed overview. Section 3 explores the potential of reinforcement learning in PET management, followed by section 4, which discusses the role of edge AI in enabling real-time and decentralized PET interventions. Section 5 examines the use of soft robotics for autonomous collection and targeted biodegradation, while section 6 presents the relevance of federated learning in supporting privacy-aware, distributed collaboration

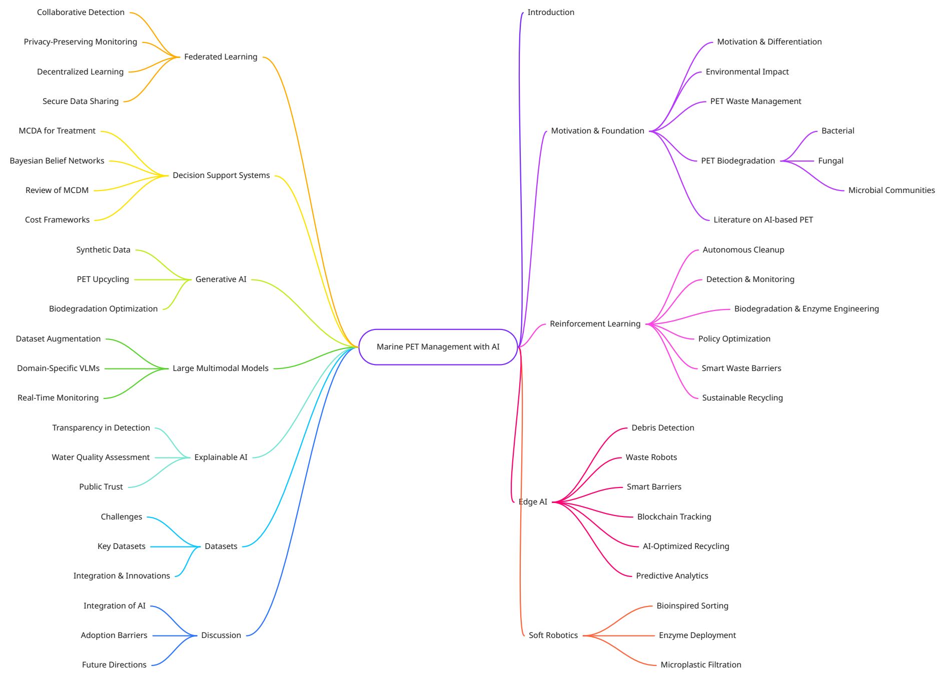

Fig. 3 The structure of the proposed review. Section numbers are shown on branches for the sake of clear presentation.

across marine monitoring systems. Section 7 covers decision support systems as integrative tools for informed PET management and policy-making, and section 8 focuses on the potential of generative AI. Section 9 investigates the emerging role of large language models (LLMs) and large multimodal models (LMMs) in synthesizing knowledge across textual and visual data sources, automating report analysis, and facilitating stakeholder communication in marine PET contexts, while section 10 covers explainable AI and its capacity to enhance transparency and stakeholder trust in AI-driven decisions. Section 11 provides an overview of available datasets relevant to the AI applications discussed. Finally, Section 12 synthesizes insights across all reviewed subfields, identifies opportunities for integration, and outlines key challenges and future research directions in AI-driven marine PET management.

2 Motivation and Conceptual Foundation

2.1 Motivation and Differentiation

To justify the need for our review, we present a twofold motivational approach. The first component of this approach is based on the analysis of co-occurrence maps created using VOSviewer. To generate these maps, we used the *Advanced Search* feature of the Web of Science (WoS) and Scopus databases. Our queries on WoS and Scopus were built as follows:

```
TS=(("plastic waste" OR "polyethylene terephthalate")
AND ("artificial intelligence" OR "machine learning" OR "deep
    learning" OR "reinforcement learning"
OR "generative AI" OR "soft robotics" OR "edge AI" OR "federated
     learning"
OR "explainable AI" OR "decision support system*" OR "computer
    vision"
OR "large language models" OR LLM)
AND ("management" OR "monitoring" OR "recycling" OR "sorting" OR
     "degradation"))
```

Listing 1 The query we used on Web of Science for retrieving relevant literature on AI technologies in PET management

```
(TITLE-ABS-KEY("plastic waste" OR "polyethylene terephthalate")
AND TITLE-ABS-KEY("artificial intelligence" OR "machine learning
    " OR "deep learning" OR "reinforcement learning"
OR "generative AI" OR "soft robotics" OR "edge AI" OR "federated
     learning"
OR "explainable AI" OR "decision support system*" OR "computer
    vision"
OR "large language models" OR LLM)
AND TITLE-ABS-KEY("management" OR "monitoring" OR "recycling" OR
     "sorting" OR "degradation"))
```

Listing 2 The query we used on Scopus for retrieving relevant literature on AI technologies in PET management

Those queries yielded 237 and 580 articles on Web of Science and Scopus, respectively, the records of which are provided in the supplementary material[1]. We then processed these records separately using VOSviewer to generate a JSON and network file pair for each of WoS and Scopus (included in the supplementary material). Each of these two file pairs indicates both the frequency of occurrence of individual terms and the frequency of co-occurrence between term pairs. In these files, the size of the node corresponding to a particular term reflects its occurrence frequency, while the link weight between any two terms represents the frequency of their co-occurrence. A co-occurrence map visualizing the information in the JSON and network files can then be plotted. The maps for WoS and Scopus are shown in Fig. 4 and Fig. 5, respectively. Later in this section, we provide a detailed analysis of these JSON and network files.

The co-occurrence maps generated from bibliographic data retrieved from Web of Science and Scopus reveal the dominance of a narrow set of AI-related terms across the literature. Terms such as machine learning, deep learning, computer vision, and object detection appear prominently at the core of both visual networks, indicating that these techniques are well-established in the context of plastic waste and environmental monitoring research. In contrast, several emerging and potentially transformative AI

[1] https://1drv.ms/f/c/19faffbe78315469/EvkqRowsfhVHpghvtAUqSuMBKZgmMVpMSyFsuM4eqZyyUw?e=lg2Ced

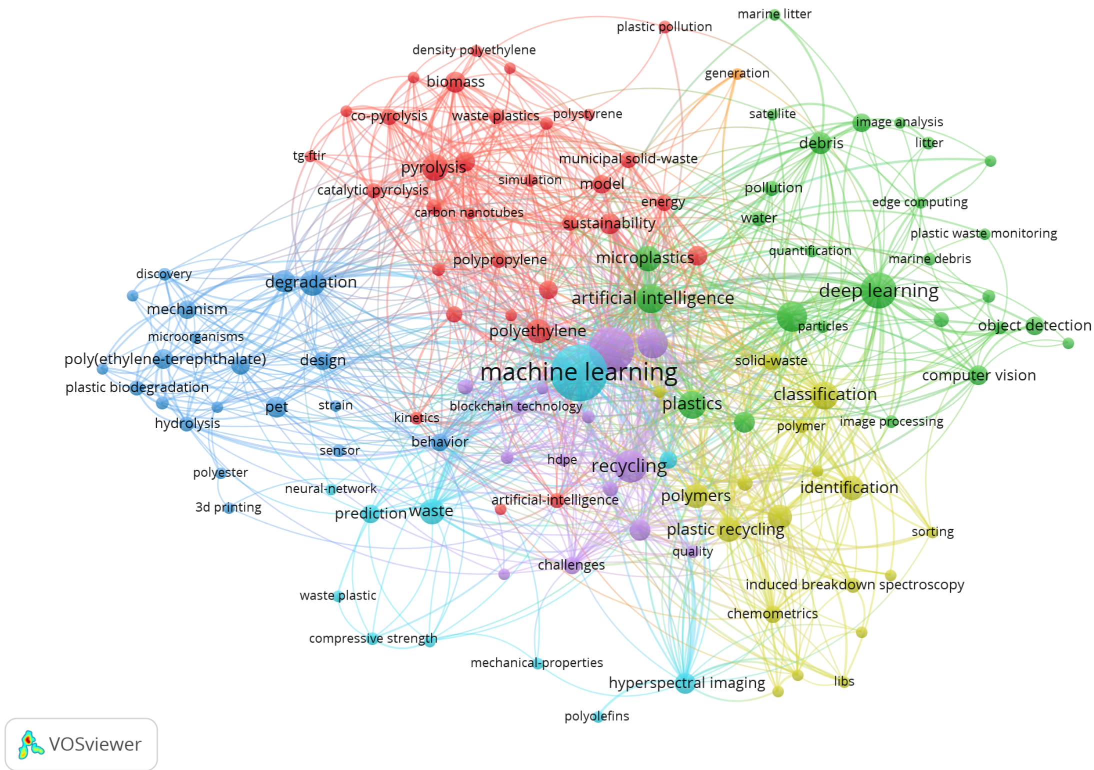

Fig. 4 A co-occurence map created by VOSviewer using bibliographic data exported from the Web of Science database. Please see text for more details. **The underlying data for reproducing this figure is available in the supplementary material.**

paradigms are either completely absent or severely underrepresented. Notably, reinforcement learning, generative AI, soft robotics, federated learning, explainable AI, and large language models (LLMs) do not appear at all, suggesting that these areas remain unexplored within this domain. A few concepts—such as edge computing and decision support systems—do appear but occupy peripheral positions in the maps, reflecting weak connectivity and marginal integration within the broader research discourse. Table 1 summarizes the presence of different AI technologies in the records of WoS and Scopus.

These observations are reinforced by the structural characteristics of the co-occurrence maps, which visually represent the information embedded in the underlying JSON and network files. The dense clustering around traditional AI methods suggests thematic saturation in certain areas, while the lack of cross-linkages to underrepresented AI concepts reflects a fragmented knowledge landscape. This visual fragmentation highlights the gap between innovation in AI and the pressing needs of sustainability-oriented research, particularly in tackling challenges such as marine PET

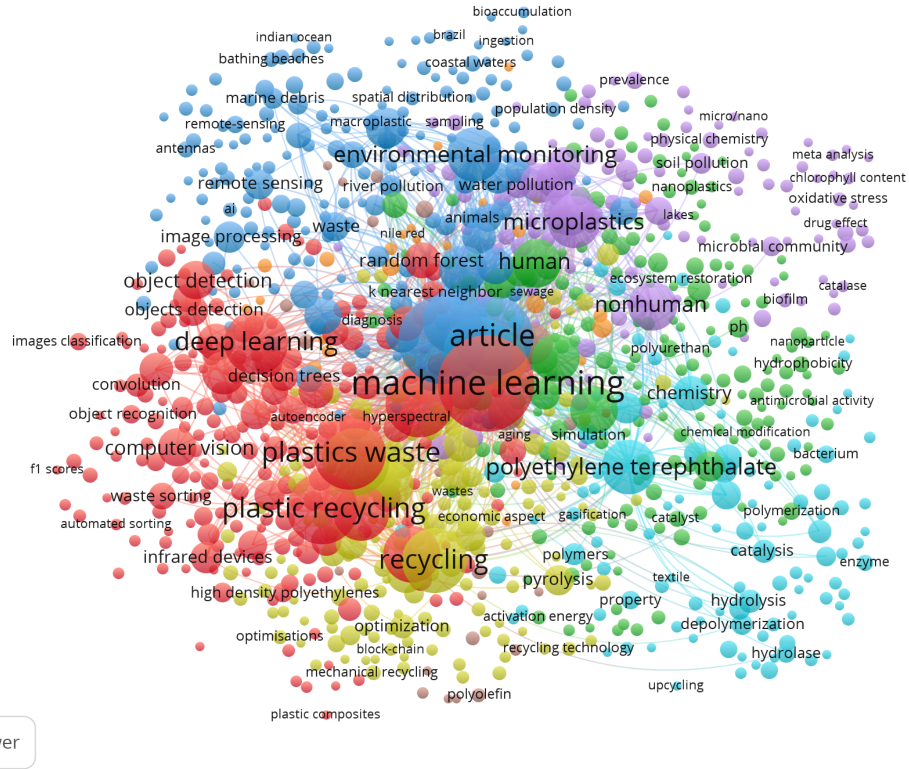

Fig. 5 A co-occurence map created by VOSviewer using bibliographic data exported from the Scopus database. Please see text for more details. **The underlying data for reproducing this figure is available in the supplementary material.**

pollution and waste management that generate hazardous micro- and nano-plastics, toxic leachates, and persistent ecotoxicological risks. The maps clearly illustrate how promising but underutilized AI techniques have yet to be conceptually integrated into existing research trajectories. As such, these visualizations provide compelling evidence of the need for a more expansive, conceptually connected investigation into the role of emerging AI technologies in environmental sustainability.

Taken together, these patterns point to a substantial conceptual gap between the mainstream AI methods that dominate current research and the emerging AI paradigms that remain largely unincorporated. The absence of linkages among these paradigms suggests a lack of thematic integration and a missed opportunity for interdisciplinary synthesis. This highlights the importance of an overview that straddles the line between a systematic review and a thematic analysis—one that not only catalogs existing contributions but also surfaces overlooked possibilities and conceptual synergies. By identifying and analyzing these gaps, the proposed study seeks to scaffold a forward-looking agenda that bridges AI innovation with marine PET management while explicitly addressing the hazardous-material dimension of PET waste accumulation and its degradation byproducts and broader sustainability goals.

Table 1 Presence of AI Technologies in Web of Science and Scopus

AI Technology	Web of Science	Scopus
Machine Learning	✓	✓
Computer Vision	✓	✓
Deep Learning	✓	✓
Reinforcement Learning	✗	✗
Edge Computing	✓	✗
Soft Robotics	✗	✗
Federated Learning	✗	✗
Decision Support Systems	✗	✓
Generative AI	✗	✗
Large Language Models	✗	✗
Explainable AI	✗	✗

The second component of our twofold motivational approach involves benchmarking a set of the most recent reviews in the field. Table 2 presents a comparison of thirteen recent and relevant review articles. To verify the absence of a comprehensive overview that encompasses the AI technologies we aim to address, we compared each review based on its stated scope, key findings, and the AI areas it covers. Our analysis reveals that most existing reviews focus on a narrow subset of AI methods, limiting readers' ability to understand how different AI technologies could complement one another—a critical consideration in many real-world contexts. More importantly, this narrow focus often overlooks emerging and impactful AI areas relevant to marine PET management.

2.2 Environmental Impact of Marine Plastics

The ecological effects of marine waste include scenarios where animals may become entangled in nets or consume plastic, posing severe threats to marine species and impacting ecosystem health (Audrézet et al, 2021). Such interactions often result in injury, disease, and death. Large maritime debris, such as abandoned fishing gear, threatens delicate marine environments like coral reefs and seagrass meadows, potentially causing significant habitat destruction (Audrézet et al, 2021). This destruction can displace native species and disrupt the delicate equilibrium of these ecosystems. Additionally, plastics and other chemical contaminants in marine debris such as bisphenols, phthalates, and heavy metal additives can disrupt the reproductive cycles of marine animals, impacting their populations and distribution.

Plastics enter the marine environment through direct inputs from ocean-related activities like aquafarming, fishing, and maritime transport. The random drift of

Table 2 A concise comparison between twelve recent reviews on AI applications in marine pollution management and waste management including detection, tracking, and monitoring. The table aims at highlighting the deficiency in the literature of reviewing the incorporation of various sub-areas of AI in PET management. Please see text for more details.

Reference	Publication Year	Concise Scope	Concise Findings	AI Areas Covered
(Ning et al, 2024)	2024	Systematic review of AI for marine pollution monitoring/-management/prediction.	AI use: 57% monitoring, 24% management, 19% prediction.	ML, deep learning, remote sensing/CV, decision support, IoT
(Ramos et al, 2024)	2024	Systematic review of ML for plastic-waste detection/classification.	CNNs dominate; detection > 80%, classification > 83%; benchmarks needed.	Deep Learning; CNN classifiers
(Moorton et al, 2024)	2024	Survey of deep-learning for marine debris detection/tracking.	YOLO often best; underwater datasets lacking; small-data underperforms.	Deep Learning; CNN classifiers, transformers
(Danilov and Serdiukova, 2024)	2024	Review of satellite/ML plastic detection in waters.	ML achieves up to 95%; key limitations include clouds, data scarcity, small targets.	Machine Learning, Remote Sensing.
(Qu et al, 2024)	2024	Review of AI-empowered microplastics collection, sorting, and characterization	AI achieves high accuracies in microplastic sorting and characterization & reduces costs	Machine Learning; Robots
(Guo et al, 2024)	2024	Advances of underwater soft robots in intelligent soft materials, fabrication, actuation, and locomotion patterns	Development of materials, actuation, and locomotion strategies inspired by marine organisms facilitated building high-performing underwater soft robots; key challenges in actuators, deep-sea robustness, power, closed-loop control.	Soft Robotics; Sensing, modeling, and control with ML/DRL
(Kowsari et al, 2023)	2023	CE + AI for marine plastics; review and soft-sensor modeling; policy.	Soft-sensor ML predicts micro/macro plastics (R=0.98/0.89); WARM shows recycling reduces GHGs.	Machine Learning; AI-based Policy Support
(Song et al, 2023)	2023	Review of AI for ocean observation, phenomena, forecasting.	Physics-guided hybrids improve consistency; ConvLSTM strong; decomposition helps.	Remote sensing, smart sensors/robots, ML/DL forecasting methods.
(Politikos et al, 2023)	2023	Review of AI for marine macrolitter; online database.	Automates classification, detection, segmentation; struggles with small, complex datasets.	UAV/satellite/camera/sonar data; ML, CNNs, object detection
(Booth et al, 2023)	2023	High-precision mapping of marine plastics	MAP-Mapper-HP achieves 95% precision in plastic detection	Deep Learning, Satellite Imagery AI
(Ditria et al, 2022a)	2022	Perspective on AI/automation for marine ecosystem monitoring.	Automation reduces costs, scales monitoring, supports adaptive conservation decisions.	Computer vision/deep learning, drones/UAVs, edge/IoT, reinforcement learning.
(Sannigrahi et al, 2022)	2022	Automated floating-plastic detection using Sentinel-2 and ML across Mediterranean sites.	RF outperforms SVM; 88–94% accuracy; FD Index most important; kNDVI helps.	Supervised ML; Remote Sensing
(Moorton et al, 2022)	2022	AI for marine debris detection without harming wildlife	Custom deep learning can distinguish debris from marine life	Deep Learning, Wildlife-Safe AI

marine plastics makes them more challenging to manage than terrestrial plastics. Approximately 98% of marine plastics originate from land-based sources, with the remainder from water activities (Gray and Weinstein, 2017). These polymers are categorized as microplastics (MPs) and nanoplastics (NPs), which are noted for causing hazardous chemical contamination and various physical and molecular damages including oxidative stress, DNA damage, and endocrine disruption in aquatic organisms. Table 1 in the referenced document provides a detailed summary of these impacts.

One of the most used synthetic plastics is polyethylene terephthalate (PET). It is produced through the polymerization of terephthalic acid (TPA) and ethylene glycol (EG), and is commonly utilized in fibers, sheets, and films. Specifically, PET is used in various industries, including electronics, automotive components, household items, lighting fixtures, power tools, sports equipment, photographic applications, X-ray sheets, and textiles. Additionally, it is widely used in food and beverage packaging, particularly for soft drinks and water bottles (Webb et al, 2012). Over 70% of soft drinks in the global market are packaged in PET bottles (Ahmaditabatabaei et al, 2021). PET exhibits various degrees of crystallinity and the majority of PET used to make bottles and textiles, has a high crystallinity of 30–40%. In contrast, PET used for packaging has less crystallinity, about 8%. PET with low crystallinity that is obtainable commercially has a crystallinity level of roughly 6-7% (Kawai et al, 2019).

Since its introduction in the 20th century for the manufacture of disposable plastic bottles, PET has been widely adopted and has become an integral part of modern society. Alongside other major plastics like polyethylene, polypropylene, polystyrene, polyvinyl chloride, and polyurethane, PET is a significant plastic, with global production reaching 56 million tons in 2013 (Kawai et al, 2019). PET has many commercial names such as Arnitel, Mylar, Rynite, Eastapac, Diolen, Hostadur, and Melinex (Webb et al, 2012). PET belongs to the polyester family, a diverse group of polymers characterized by the presence of ester functional groups in their macromolecular backbones (Fakirov, 2017). The recycling of PET has gained attention due to its resistance to natural degradation. PET products decompose at a very slow rate in the environment leading to long-term persistence, accumulation of hazardous degradation fragments, and chronic ecotoxicological exposure pathways.

2.3 PET Waste Management

The recycling of Polyethylene Terephthalate (PET) has been promoted since it is very recalcitrant (Highly resistant to natural decay) to natural deterioration. PET, commonly used in packaging, decomposes naturally at a slow rate, making it a significant contributor to long-lasting environmental waste and a hazardous source of persistent pollutants in marine ecosystems.

Currently, the primary methods for managing PET waste include physical and chemical recycling, landfilling, and incineration. 'Physical recycling' involves mechanically processing plastics to create new products, while 'chemical recycling' breaks plastics down chemically to form raw materials. 'Landfilling' refers to the disposal of waste in landfill sites, and 'incineration' involves burning waste materials to reduce their volume.

These disposal techniques have significant environmental drawbacks, including the release of hazardous contaminants and toxic byproducts such as heavy metals, dioxins, furans, and volatile organic compounds, secondary environmental pollution, significant climate change, and concerns for human health and safety (Sharifian and Asasian-Kolur, 2022). In addition, it requires substantial amounts of energy, which is neither practical nor environmentally sustainable due to inadequate recycling methods (Derraik, 2002).

Given these challenges, recycling presents a more sustainable alternative to address the growing accumulation of PET waste. Among the various methods, mechanical recycling is one of the most widely used for large-scale plastic waste management. However, current PET waste recycling is highly inefficient, resulting in low-quality recycled PET. This inefficiency is due to mechanical stress during processes such as segregation, grinding, crushing, re-extrusion, reprocessing, and photo-oxidation caused by the heat of fusion (Sinha et al, 2010). Notably, there have been no reports of microplastic production during mechanical recycling to date though mechanical abrasion poses latent risks of secondary microplastic release if processes are uncontrolled.

Chemical-based recycling processes for PET waste involve breaking down PET into products with lower molecular weights. These processes include glycolysis, alcoholysis, and hydrolysis, which use strong acids and alkalis to react with water. Alcoholysis also involves the use of alcohol, ethanol, and methanol. Although PET can be depolymerized through chemical-aided recycling, the process requires high temperatures and pressures, leading to the evolution of toxic byproducts and significant secondary pollution such as corrosive effluents, hazardous intermediates like BHET, and uncontrolled emissions. As a result, chemical-based recycling is generally not recommended. Figure 4 summarizes the current processes used to manage PET waste (Khairul Anuar et al, 2022).

Given the robust mechanical properties of plastic materials, significant environmental challenges have emerged, including soil contamination and the disruption of marine ecosystems (Danso et al, 2019). Consequently, PET biodegradation has garnered attention as an environmentally friendly alternative, as it consumes less energy and operates at lower temperatures compared to other recycling methods while minimizing the hazardous outputs associated with conventional recycling.

2.4 PET Biodegradation

In 1977, it was reported that numerous commercial lipases and esterases hydrolyzed different types of polyesters. Since then, numerous microbes have been identified, and consequently, several enzymes have been isolated and characterized, including multiple PET hydrolases such as lipases, cutinases, and esterases. In 2016, Tanasupawat et al. (Tanasupawat et al, 2016) discovered the Ideonella sakaiensis 201-F6 strain in a trash recycling facility (Danso et al, 2019), which was found to produce PET hydrolase (PETase) and mono hydroxyethyl terephthalate (Qi et al, 2021).

The six polymers most used in plastic production include polyethylene (PE), polypropylene (PP), polystyrene (PS), polyvinyl chloride (PVC), polyethylene terephthalate (PET), and polyurethane. Microorganisms are known to naturally degrade these synthetic polymers and biotransform them into products with added value. As a result, scientists are exploring the use of microbes for the degradation of synthetic materials like plastics. It is suggested that microorganisms may be evolving to adapt to life in the plastic age. Figure 1 shows a comparison of the different organic structures of various types of synthetic plastics.

Biodegradation of plastic involves the depolymerization of polymeric materials into oligomers or monomers, which can then enter the biogeochemical cycle. Various enzymes catalyze these biodegradation processes (Skariyachan et al, 2022). The complete biodegradation process consists of four stages: deterioration, fragmentation, assimilation, and mineralization. Figure 6 illustrates the microbial degradation mechanism of plastics.

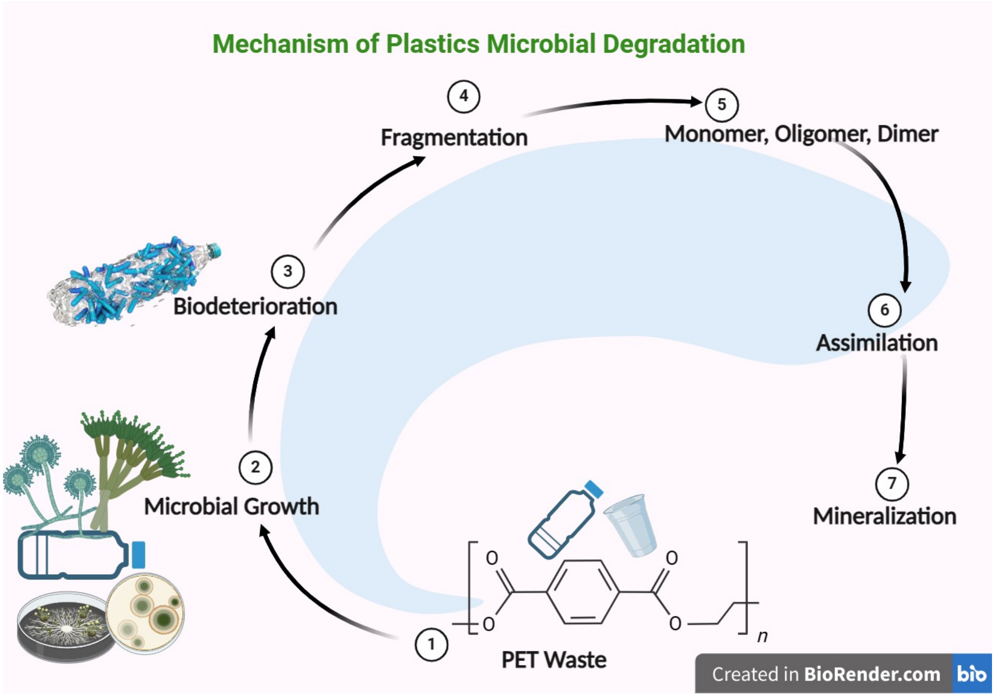

Fig. 6 The mechanism of microbial degradation of plastics

2.4.1 Bacterial Biodegradation

In 2016, a Japanese research team discovered Ideonella sakaiensis within a contaminated site with PET bottles (Yoshida et al, 2016). This bacterium was found to degrade PET by producing enzymes and utilizing PET as a carbon source, offering a promising solution to the global PET degradation challenge. A recent study (Walter et al, 2022) highlighted its ability to degrade two types of plastic containers with a degradation efficiency of 96%.

Ideonella sakaiensis degrades PET through a series of steps, starting with attachment to the PET surface, followed by enzyme production, metabolism, and energy generation. The bacterium's initial physical attachment is facilitated by environmental conditions, PET's hydrophobic properties, and the production of adhesion molecules with a high affinity for PET. Additionally, the bacterium forms a biofilm, producing a matrix of extracellular polysaccharides (EPS) that further aids in adhesion. Once attached, Ideonella sakaiensis produces two key enzymes: membrane-bound MHET hydrolase (MHETase) and extracellular PET hydrolase (PETase) (Graf et al, 2021). The PETase enzyme hydrolyzes PET, yielding terephthalic acid (TPA), ethylene glycol, and monomers of mono(2-hydroxyethyl) terephthalate (MHET). MHETase enzyme then hydrolyzes MHET into TPA and ethylene glycol. Through enzyme production and metabolic pathways like glycolysis, the bacterium completes the breakdown of PET, assimilating these monomers as carbon sources to generate energy.

Moreover, Marine bacteria have been recognized for their widespread applications in biodegradation (Viel et al, 2023; Zhao et al, 2023). Recent research has highlighted the ability of the marine bacterium Rhodococcus pyridinivorans to degrade PET (Zhao et al, 2023). The bacterium produces PET esterase, which catalyzes PET degradation. Under certain conditions, studies have documented the degradation of 4.03 mg of PET within five weeks of culture. High-performance liquid chromatography (HPLC) analysis confirmed the production of MHET and TPA as the primary degradation products, while BHET was identified as a temporary product that rapidly converts to MHET.

Additionally, further screening of the same environment revealed the coexistence of other bacterial species with PET degradation capabilities, including Burkholderia (Jiang et al, 2023), Paraburkholderia, Caballeronia, Mycobacterium, Cupriavidus, Variovora, Bradyrhizobium, Hydrogenophaga, Novosphingobium, Achromobacter, Sphingopyxis, and Acidovorax_D, among others.

Furthermore, (Din et al, 2023) documented a new isolate, Stenotrophomonas maltophilia PRS8, which demonstrates the ability to degrade PET at mesophilic temperatures. This degradation process is facilitated by biofilm formation on the PET surface and the production of a cutinase-like enzyme. Optimization of physicochemical factors has enhanced enzyme production, yielding terephthalic acid (TPA), mono(2-hydroxyethyl)-TPA (MHET), and bis(2-hydroxyethyl)-TPA (BHET). Stenotrophomonas maltophilia PRS8 shows promise as a solution for PET degradation, exhibiting similar results to Ideonella sakaiensis and outperforming the Humicola insolens thermostable HiCut (HiC) enzyme (Ahmaditabatabaei et al, 2021).

Another study highlighted the Symbiotic relationships that occur between organisms that can benefit, harm, or have no effect on each other. Xanthomonas sp. HY-74 and Bacillus sp. HY-75 within the insect gut demonstrates such a relationship. A novel study (Kim et al, 2023) isolated Xanthomonas sp. HY-74 and Bacillus sp. HY-75 and highlighted their ability to produce enzymes with potential for PET degradation. The study observed PET weight loss and morphological changes using a scanning electron microscope (SEM).

2.4.2 Fungal Biodegradation

Aspergillus species are known for their enzyme production capabilities (Ntana et al, 2020). A recent study (Esmaeili Nasrabadi et al, 2023) focused on Aspergillus spp. and their efficiency in removing or degrading PET, HDPE, LDPE, PE, PU, and PVC. Aspergillus glaucus and Aspergillus niger exhibited a high PET degradation/removal rate of 40%, while Aspergillus flavus, Aspergillus niger, and Aspergillus oryzae showed moderate efficiencies, with degradation rates of 28.78% and 26%, respectively.

Another study focusing on microorganisms with enzymatic activities potential for PET depolymerization (Malafatti-Picca et al, 2023) found that Trichoderma sp. CBMAI 2071, Trichoderma atroviride CBMAI 2073, Cladosporium cladosporioides CBMAI 2075, and Curvularia trifolii CBMAI 2111, demonstrated enzyme production, chemical alterations, polymer structure modifications, and the release of monomers and oligomers.

Also, a novel study (Sales et al, 2023) tested the ability of Yarrowia lipolytica IMUFRJ 50682 to depolymerize PET from waste mooring lines of Oil & Gas offshore platforms. Promising results were observed, including the production of PET monomers and their intermediates as end products, as well as increased PET crystallinity and surface deformation due to biodegradation.

2.4.3 Microbial Communities Degradation

The diversity of the bacterial community in the deep sea offers promising potential for PET degradation. A research study on oceanic deep-sea sediments reported PET weight loss after inoculating PET films with colonization by M. sediminum, M. gudaonensis, T. xiamenensis, and N. marinus (Zhao et al, 2023). Additionally, the study detected MHET and TPA monomers as end products of PET depolymerization.

Furthermore, a recent research study (Maheswaran et al, 2023) prepared microbial consortia (MC) consisting of two bacterial isolates, Bacillus subtilis and Sarcina aurantiaca, along with two fungal isolates, Aspergillus flavus and Aspergillus niger. The consortia demonstrated the potential to degrade PET without pretreatment, as well as decreased the crystallinity and hydrophobicity of PET films, resulting in a weight loss percentage of 28.78%.

It is worth noting that, microbial synergistic interaction occurs when two microorganisms collaborate to achieve an overall performance and functionality that exceeds what either organism could accomplish individually. In this context, the research in (Yan et al, 2023) has reported synergism between P. nitroreducens S8 and P. monteilii S17, which offers a promising pretreatment application for PET degradation by forming biofilm and enhancing the process through PET surface distortion.

2.5 A Glance on the Literature of AI-based PET Biodegradation, Detection, and Sorting

Artificial intelligence (AI) has significantly transformed polyethylene terephthalate (PET) waste management by enabling breakthroughs in both biodegradation optimization and waste handling efficiency. In the domain of biodegradation, deep learning (DL) has played a vital role in enzyme discovery and protein engineering. Machine learning models—such as convolutional and recurrent neural networks—are now used to predict enzyme-substrate interactions, leading to the identification of highly efficient PET-degrading enzymes such as PETase and MHETase (Salas-Nuńez et al, 2024; Kroll et al, 2023). Genomic prediction models supported by neural networks and support vector machines (SVMs) simulate genetic variations and forecast enzymatic activity (Jin et al, 2023), thus expediting the design of chimeric enzymes with enhanced activity, specificity, and environmental stability (Ferreira et al, 2023).

These models are further strengthened by metagenomic analysis (Purohit, 2020), which allows researchers to mine large environmental datasets for novel PET-degrading organisms. The synergy between in-silico predictions and in-vitro validation has accelerated the development of bio-catalytic systems for PET depolymerization under diverse marine conditions (Markus et al, 2023). Additionally, enzyme formulation technologies leverage generative models and high-throughput screening to optimize catalytic efficiency, even in fluctuating pH and temperature conditions (Xie and Warshel, 2023; Wen et al, 2025). Recent reviews have also noted the rising contribution of generative adversarial networks (GANs) in proposing novel enzyme variants, thereby deepening the integration of AI into molecular biodegradation pathways (Gelfand et al, 2025).

In parallel, computer vision (CV) and machine learning (ML) approaches have been widely deployed to automate the detection, classification, and sorting of PET waste. For example, marine waste segmentation models trained on datasets such as TrashNet and MODSD enable autonomous underwater vehicles (AUVs) to detect PET items in diverse aquatic conditions (Khriss et al, 2024). Enhanced convolutional neural networks (CNNs) have been shown to support microplastic detection at scale, even in turbid or low-light marine environments (Gugliandolo et al, 2024; Sarker et al, 2024). Similarly, real-time waste classification in recycling facilities benefits from edge AI-powered object detection algorithms that operate on conveyor belts, allowing for rapid separation of recyclable PET from other debris (Satav et al, 2023; Cheng et al, 2024).

Recent works also highlight smart systems that integrate RFID/GPS tags and IoT sensors to support PET waste tracking across the collection, recycling, and distribution chain. These systems, coupled with blockchain infrastructure, enable provenance tracing and improved accountability in circular economy models (Alnuaimi et al, 2023; Bułkowska et al, 2024). Furthermore, sorting technologies based on DL and resin identification codes (RICs) now allow for material-specific classification of PET composites, improving recycling purity and resource recovery (Kunwar et al, 2025).

A quick glance at the recent literature confirms this wide adoption of core AI technologies. For example:

- Plastic litter detection using CNN-based classifiers in marine environments (Khriss et al, 2024)
- Generative augmentation for underwater waste datasets using CycleGANs (Khindkar and Khindkar, 2022)
- PET enzyme engineering using ML-guided hydrolase design (Lu et al, 2022)
- Deep learning-based PET waste classification using RICs (Kunwar et al, 2025)
- Smart robotic sorting and detection for PET using integrated AI pipelines (Satav et al, 2023)

These examples collectively highlight the *technological maturity* of ML, DL, and CV in PET biodegradation and handling. Consequently, these approaches have become the cornerstone of AI in plastic waste management.

With this context established, the remainder of this review turns its attention to underexplored AI methodologies—such as reinforcement learning, generative AI, federated learning, and soft robotics. These emerging fields, although nascent, hold untapped potential to address existing bottlenecks in marine PET management. To provide a high-level overview, Fig. 7 presents a Sankey diagram that envisages a mapping of the major capability clusters identified in PET management to the emerging AI paradigms most relevant to enabling them. This visualization highlights the key connections between paradigms and their distinctive strengths, serving as a conceptual bridge into Section 3 and the following sections, where each paradigm and its capabilities will be discussed in detail.

3 RL for PET Waste Management in Marine Environments

3.1 Detection and Monitoring of PET Waste in Marine Ecosystems

Artificial intelligence (AI)-driven satellite and aerial surveillance systems can use reinforcement learning (RL) to improve the identification of floating PET debris from high-altitude balloons, aerial drones, and satellite data. Furthermore, RL-enhanced sonar and LiDAR systems can be taught to distinguish PET trash from naturally occurring ocean components including seaweed, boulders, and marine life. This can help in prioritizing high-risk debris likely to fragment into micro/nano-plastics. Through learning from real-time environmental data, such as temperature changes, wind patterns, and ocean currents, these RL-optimized remote sensing algorithms get better over time, making it possible to anticipate garbage accumulation areas with greater accuracy. Dynamic forecasting of PET waste drift is another critical application of RL.

With RL-based technology, underwater PET waste identification is also progressing. In deep-sea settings, underwater robots using RL-powered computer vision systems are able to identify and categorize submerged PET trash. As an example of the research in this domain, the researchers in (Zhang et al, 2023b) proposed a deep learning model to identify marine debris in images captured by remotely operated vehicles (ROVs). The model employs convolutional neural networks (CNNs) to recognize and classify objects, aiming to enhance the effectiveness of ocean cleanup initiatives. This approach highlights the potential of AI-driven technologies in addressing the challenges of marine pollution detection and mitigation. Following identification, it is essential to ensure effective collection and cleanup processes.

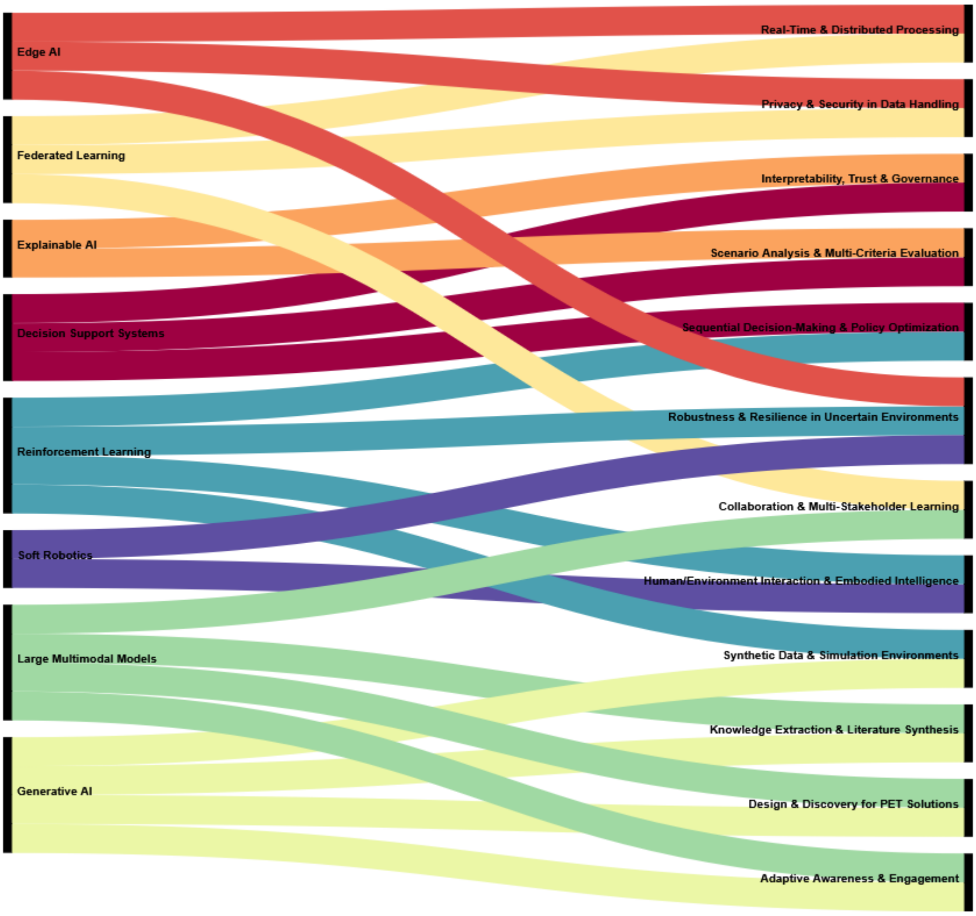

Fig. 7 Sankey diagram illustrating the high-level connections between clustered PET management capabilities and the emerging AI paradigms that enable them, highlighting overlaps and complementarities across approaches.

3.2 Autonomous Marine Waste Collection and Cleanup

Floating and submerged PET debris release hazardous additives and toxic leachates (e.g., phthalates, bisphenols) into water columns. By integrating reinforcement learning (RL) technology, autonomous marine garbage collection and cleaning systems are becoming more advanced, reducing exposure of marine organisms and humans to these hazardous compounds, and mitigating downstream ecotoxicological risks. Moreover, by integrating data from buoys, satellites, and oceanographic sensors, RL improves oceanic drift prediction models. This allows for proactive cleanup efforts before waste reaches sensitive ecosystems, minimizing environmental damage.

In order to gather floating or submerged PET trash, marine robots—such as autonomous surface vehicles and underwater drones—can use RL-based algorithms to traverse constantly shifting ocean currents. In order to ensure effective and focused cleaning operations, these algorithms allow the robots to select collecting zones based on oceanographic models and real-time pollution concentrations. By allowing swarms of self-governing boats and drones to coordinate their routes for the best possible collection of PET waste, multi-agent RL significantly improves the efficacy of these systems. These systems may adjust to new marine PET contamination hotspots using self-learning collecting techniques, increasing their reactivity and general effectiveness. Inspired by this potential, the research in (Nader et al, 2024) proposes a robust solution for object retrieval in dynamic marine conditions. The study employs a deep reinforcement learning (DRL) algorithm called Soft Actor-Critic (SAC) to train an agent for retrieving objects from a dock despite disturbances caused by sea waves. This approach demonstrates the potential of RL in addressing complex challenges in marine environments, paving the way for more effective and adaptive waste collection systems.

3.3 Biodegradation and Enzyme Engineering for PET in Marine Conditions

Innovative approaches for the management of PET waste can be provided by the application of reinforcement learning (RL) to optimize marine biodegradation processes. By using PET-degrading bacteria or enzymes, such as PETase and MHETase, in regulated marine habitats, RL can improve bio-remediation techniques by hastening PET breakdown while taking into account toxic intermediates (e.g., BHET, MHET) that can act as hazardous byproducts. Particularly, RL has the potential to maximize the effectiveness of these biological processes by adjusting variables like salinity, pH, and enzyme concentration after learning the ideal conditions for microbial breakdown.

Along the same lines, new PET-degrading enzymes that are suited to work well in harsh marine environments, including low oxygen levels, high salinity, or cold temperatures, can be developed in the field of protein engineering using RL-based generative design. This is not only as efficiency enhancement but also as hazard-mitigation through enzyme safety profiles. Moreover, PET biodegradation rates can be greatly increased by RL-driven molecular simulations, which further enhance these enzymes by forecasting and optimizing enzyme-substrate interactions.

One example of research areas that can benefit from RL was highlighted in (Râpă et al, 2024a). This study examines the distribution and identification of marine plastic waste, assesses its socio-economic and environmental impacts, and explores recovery strategies from a circular economy perspective. The comprehensive analysis, presented in this study, highlighted the domain of automatic and rapid classification of micro-plastics in images, which can benefit significantly from RL-optimized biodegradation and protein engineering. This addresses the growing challenge of marine plastic pollution sustainably.

3.4 Prevention Strategies Using RL-Based Policy Optimization

Reinforcement learning (RL) can be used to improve smart fishing gear and vessel incentive systems to motivate fisherman and cargo ships to collect PET trash they come across while operating. By constantly modifying reward-based collection programs according to current garbage levels and economic considerations, RL can maximize incentive mechanisms, guaranteeing increased involvement and efficacy in lowering marine plastic pollution and hazard reduction. This is closely related to the potential of RL in building predictive models for marine trash restrictions and in simulating long-term hazard accumulation scenarios. By capitalizing on these technologies, governments can forecast the long-term effects of policies like deposit-return schemes, extended producer responsibility (EPR), and plastic bans.

In order to create more equitable and successful international policies to address marine plastic pollution, RL-based models can evaluate trade-offs between industry restrictions and economic costs. The researchers in (Almroth and Eggert, 2020) provide an overview of plastic materials, their environmental impacts, and the challenges posed by marine plastic pollution. The article highlights the effects on marine ecosystems and human health, discusses policy and technical issues, and identifies research priorities. It emphasizes the need for innovative solutions, which can incorporate RL-optimized incentive programs and predictive policy models, to address the growing issue of marine plastic pollution effectively.

3.5 Smart Waste Barriers and Oceanic PET Containment

Reinforcement learning (RL) can revolutionize adaptive floating barriers and booms, allowing real-time optimization of PET collection devices like as those utilized in the Ocean Cleanup project (The Ocean Cleanup, 2013). To maximize their effectiveness, RL algorithms can be incorporated to modify the locations of these barriers in response to weather, garbage accumulation trends, and ocean currents. To further improve their usefulness, these systems may also be outfitted with AI-driven robotic arms that autonomously separate PET trash from biological materials using reinforcement learning. Reinforcement learning can also be useful for dynamic, proactive river interception systems, which aid in the development of AI-powered solutions to stop PET waste from entering the ocean and intercept PET before it fragments into hazardous micro- and nano-scale pollutants that enter food webs. In order to provide proactive and efficient pollution management, smart RL-powered hydrodynamic models has the potential to forecast the best places to capture garbage in rivers and estuaries before it joins bigger bodies of water. The researchers in (Khriss et al, 2024) critically evaluate recent advancements in using convolutional neural networks (CNNs) and other machine learning techniques to detect and measure plastic debris in water bodies. While this review examines models, datasets, and evaluation metrics, it underscores the potential of AI-driven technologies in improving the interception of marine plastic pollution, in which RL can be of a central importance, contributing to more sustainable environmental management practices .

3.6 Sustainable Marine PET Recycling

A balanced and profitable recycling ecosystem may be ensured by RL's ability to do the following: 1) evaluating the viability of several PET recovery techniques, including chemical and mechanical recycling, and suggesting the most environmentally friendly options, 2) and dynamically modifying pricing models for recycled PET (rPET) in response to supply-demand dynamics and environmental factors. Reinforcement learning can also play a crucial role in supply chain optimization for marine PET recovery. Hence, it reduces expenses and maximizes environmental benefits by streamlining the logistics of collecting, transporting, and processing PET trash from isolated coastal areas to recycling plants. This is often referred to as self-learning supply chain models.

In addition to adapting to changing conditions and ensuring sustainable operations, self-learning supply chain models can recommend hazard-minimizing recycling pathways. This, for instance, is pivotal for preventing unsafe shipment of PET waste to poorly regulated facilities that release hazardous emissions. While many researchers have explored the valorization of marine plastic litter (through chemical and mechanical recycling), the review in (Râpă et al, 2024b) highlights the role of policy support in reducing marine plastic pollution and emphasizes the need for a holistic and sustainable approach. By integrating RL-optimized recovery and supply chain strategies, this approach not only mitigates the environmental impact of marine plastic debris but also creates economic opportunities, aligning with broader sustainability goals.

Table 3 features a comparison of the capabilities of RL vs. traditional AI technologies.

Table 3 Comparison of Capabilities: Reinforcement Learning vs. Traditional AI

Capability	**Traditional AI (ML/DL/CV)**	**Reinforcement Learning (RL)**
Sequential decision-making in dynamic environments	✗	✓
Policy optimization under uncertainty	✗	✓
Real-time adaptation and continuous learning	Limited	✓
Multi-agent collaboration and decentralized control	✗	✓
Gamified incentive design and behavioral modeling	✗	✓

4 Applications of Edge AI in Marine PET Management

4.1 Smart Marine Debris Detection and Classification

An inventive method for identifying and categorizing marine garbage, especially PET waste, can be offered by the combination of cutting-edge AI technology with IoT-enabled marine sensor networks. PET trash can be tracked and monitored in real time thanks to autonomous buoys and floating sensors that are outfitted with spectral sensors, LiDAR, and AI-powered cameras. These devices reduce latency and the requirement for constant cloud connectivity by processing image and video data locally using Edge AI. The precision of identifying PET trash, whether it is floating on the surface or submerged underwater, is further improved by multi-sensor fusion, which combines ultrasonic, radar, infrared, and optical technologies. These marine sensors are complemented by AI-powered aerial drones that locate PET waste hotspots in rivers, seas, and coastal areas.

A key characteristic of these various sensing platforms lie in its ability to use Edge AI models to categorize marine waste in real-time instead of sending massive amounts of raw data to the cloud. This framework increases energy efficiency while simultaneously accelerating the detecting procedure. Furthermore, drones can accurately identify PET plastic from biological materials like seaweed thanks to AI-driven spectral analysis. The authors of (Singh et al, 2023) investigated the detection of microplastic trash in maritime settings using edge computing and computer vision techniques. The article presents a real-time microplastic identification approach based on enhanced convolutional neural networks (CNNs). This approach aims to enhance waste detection in oceans and rivers while operating efficiently with minimal connectivity requirements, demonstrating the potential of edge-based solutions in combating marine pollution.

4.2 Autonomous Waste Collection Robots

Following detection and classification, a major step forward in combating marine pollution is represented by AI-driven marine cleanups. Beyond examining PET density and ocean currents, Edge AI can be utilized by IoT-enabled autonomous boats to navigate and optimize garbage collecting routes. This is crucial for retrieving hazardous PET items in sensitive zones.

Fleets of marine robots may work together dynamically and cover more regions more effectively thanks to swarm robotics, which is improved by decentralized Edge AI processing. Furthermore, real-time edge-based material classification algorithms are used by AI-powered robotic arms on collection boats to separate PET plastics from other debris, increasing the overall effectiveness of cleanup efforts. Drones that are capable of gathering rubbish underwater improve these initiatives even further. Through the use of edge computing, these drones provide more efficient garbage removal by lowering reaction times and instantly modifying collection plans in response to environmental variables like tides and underwater currents. PET trash on the seafloor may be found using IoT-enabled Remotely Operated Vehicles (ROVs) outfitted with Edge AI-powered sonar and image recognition systems.

One example of the research in this direction is the work proposed by (Sahoo et al, 2020). A robotic fish system for collecting and detecting garbage underwater is built to identify and eliminate non-biodegradable garbage effectively. The system combines mobile edge computing, sophisticated image processing, optical biosensors, and cameras. By tackling the problem of marine trash in a sustainable and cutting-edge way, this creative strategy seeks to preserve undersea habitats and support environmental conservation. Moreover, fast and localized decision-making prevents hazardous materials from dispersing into fishery food chains and thus reduces human exposure risks.

4.3 Predictive Analytics and Decision Support for Marine Cleanup Operations

In order to identify PET accumulation zones, AI-driven ocean pollution forecasting systems use Edge AI-powered IoT buoys to gather real-time oceanographic data, including tides, temperature, and salinity. When paired with AI-powered simulation models, these systems are able to predict how PET contamination would affect marine biodiversity and suggest specific cleanup efforts to lessen harm. The effectiveness of marine conservation initiatives is increased by this proactive approach. By offering practical insights, intelligent decision support technologies provide stakeholders even more leverage.

For government organizations, non-profits, and waste management firms, real-time PET pollution heatmaps are produced using IoT-integrated dashboards driven by Edge AI analytics. Additionally, AI-driven policy recommendations help optimize marine plastic regulations and resource allocation, ensuring more effective PET waste management strategies. The authors of (Ditria et al, 2022b) examined the role of AI and automation in marine science. The article emphasizes how predictive modeling and decision support systems, powered by AI-driven analytics, can enhance the planning and execution of marine cleanup operations. By delivering real-time insights and forecasts, these technologies contribute to more informed and efficient conservation efforts, ultimately supporting the protection of marine ecosystems.

4.4 Smart Waste Barriers and Marine Waste Containment

Similar to RL (please see section 3.5), Edge AI can be used to build smart waste barriers. Particularity, Edge AI can empower the dynamic change of floating barriers' locations in response to real-time data from IoT sensors. Optimal operation, through effective anticipation of PET trash formation, can also benefit from feeding the information of IoT-connected flow sensors into AI algorithms. By categorizing PET trash and sending out signals when collection is necessary, solar-powered floating barriers with Edge AI cameras further improve functioning and guarantee prompt and focused cleanup efforts.

Along the same lines, Edge AI can optimize the operation of river skimmers and the movement of interception arms by analyzing data on trash accumulation and water flow, lowering operating costs and energy consumption while preserving high efficiency. A notable research in this point is (Miller et al, 2025) where researchers looked at how AI-enhanced IoT systems boost data gathering, analysis, and decision-making processes in managing environmental pollution, particularly maritime trash containment, and highlights examples like smart waste barriers. This integration shows how cutting-edge technology may efficiently and sustainably solve environmental concerns.

4.5 PET Waste Tracking and Blockchain Integration

IoT-enabled smart PET waste monitoring systems represent one creative approach to monitoring and controlling plastic pollution, especially with regards to identifying high-hazard PET waste flows. Authorities may identify the origins of PET trash with the use of IoT-enabled waste tracking tags, such as RFID, GPS, or blockchain-based systems, improving accountability and facilitating focused actions. By guaranteeing transparency and traceability in the recycling process, blockchain-supported circular economy models enhance waste management initiatives even more.

In order to provide useful information for mitigation methods, Edge AI sensors at recycling stations can be used to scan incoming debris and use pattern recognition algorithms to anticipate the sources of marine plastic pollution. Moreover, AI-powered waste tracking, combined with blockchain technology, creates a transparent supply chain for recycled PET. Consumers and manufacturers can scan QR codes on PET products to access detailed information about the waste's origin, recycling history, and environmental impact, fostering greater awareness, responsibility, and trustworthiness.

In (Popescu et al, 2024), the authors emphasized the potential of integrating blockchain technology to improve data transparency and traceability in waste management systems. This approach is particularly relevant for PET waste tracking in marine environments, demonstrating how advanced technologies can contribute to more effective and sustainable pollution management. It is worth mentioning that blockchain-based provenance records can document hazardous emissions avoided when PET is recycled safely rather than incinerated or landfilled.

4.6 AI-Optimized Marine PET Recycling

Edge AI can be used by smart sorting systems with recovered PET trash to expedite the separation and recycling procedure. Sorting ensures hazardous PET streams (e.g., colored, multi-layered bottles with toxic stabilizers) are identified and treated separately to prevent contamination of recycled products. Conveyor belts driven by AI automatically separate PET trash from other marine debris on marine cleaning vessels or in recycling facilities. By separating premium PET that can be recycled from deteriorated or useless plastic, real-time AI classification algorithms operating on edge devices further increase efficiency and guarantee the best possible resource recovery.

These possibilities are expanded to far coastal areas by IoT-controlled mobile recycling devices. Based on the properties of incoming garbage, solar-powered mobile recycling stations work independently, optimizing mechanical and chemical PET recycling operations with AI-driven edge analytics. Additionally, smart inventory tracking systems help balance the supply of collected PET waste, preventing overloading of processing facilities and ensuring smooth operations.

Table 4 features a comparison of the capabilities of Edge AI vs. traditional AI technologies.

5 Soft Robotics: Bioinspired Solutions for Marine PET Management

Soft robotics, a field inspired by the flexibility and adaptability of natural organisms, offers innovative solutions for PET waste management in challenging aquatic environments. Unlike traditional rigid robots, soft robots use pliable materials, allowing them to interact safely with sensitive ecosystems. Hence, soft robots can reduce the release of secondary microplastics that occurs when brittle, aged PET fragments are mishandled — preventing further hazardous particle dissemination. Soft robotics has proven

Table 4 Comparison of Capabilities: Edge AI vs. Traditional AI

Capability	Traditional AI (ML/DL/CV)	Edge AI
Real-time inference in remote, low-connectivity environments	✗	✓
On-device processing with reduced latency and energy use	✗	✓
Autonomous actuation based on sensor input (e.g., drones, robots)	✗	✓
Privacy-preserving operation without data transmission	Limited	✓
AI-powered continuous monitoring in dynamic field conditions	Limited	✓
Closed-loop control and localized decision-making	✗	✓

effective in tasks ranging from waste collection to biodegradation and recycling. We dedicate this subsection to discussing a few potential uses of SR in marine PET waste management.

5.1 Bioinspired Waste Collection and Sorting

One of the most promising uses of soft robotics in PET management is bioinspired waste collection. Robots modeled after marine organisms, such as jellyfish and octopuses, can navigate complex underwater environments—such as coral reefs and seabeds—while minimizing ecological disturbances. Equipped with flexible, soft grippers, these robots can gently capture PET waste without harming marine life. Thus, soft robots' gentle handling minimizes aerosolization or leaching of these toxins. Their ability to adapt to irregular surfaces and currents allows them to surpass the efficiency of rigid robotic systems in removing debris from diverse underwater landscapes.

Notable studies exploring the design of SR were presented in (Wang et al, 2022; Youssef et al, 2022). They investigated bioinspired designs and the latter emphasized the advantages of soft robotic grippers in securely grasping plastic debris while preventing damage to marine habitats.

Soft robotics can also transform operations in recycling facilities. Equipped with AI-driven vision systems, these robots excel in sorting PET waste by type, color, or condition. Their flexibility allows them to handle diverse materials gently, preventing contamination and improving the efficiency of recycling processes. By integrating soft robotics with AI, facilities can achieve higher throughput and accuracy in waste sorting and processing (Akram et al, 2024; Cheng et al, 2024). Along the same line of sensor-equipped soft robotics, AI-enabled hazard classification sensors (e.g., chemical sniffers or spectroscopic attachments) could be integrated into soft grippers to differentiate benign PET items from hazardous PET fragments coated with toxic substances.

5.2 Enzyme Deployment for Biodegradation

Another emerging strategy involves the use of soft robotics to facilitate enzyme-based PET biodegradation. Uncontrolled biodegradation of PET can yield hazardous intermediates (e.g., bis(2-hydroxyethyl) terephthalate, terephthalic acid at toxic levels). In this regard, soft robots can transport and release specialized enzymes capable of breaking down PET waste in targeted locations, particularly in high-density pollution zones. By focusing on strategic deployment, this method accelerates the degradation process and reduces the environmental footprint of PET pollution. Additionally, integrating AI-powered navigation enhances the precision of enzyme distribution, ensuring maximum effectiveness.

A promising research direction could be the exploration of soft robots that are engineered to carry enzymatic solutions to specific underwater waste sites. The role of robotic mobility and AI optimization would ensure efficient and sustained enzyme activity in marine environments. A promising direction in deploying soft robots, beyond their usage as enzyme carriers, is their potential as hazard-neutralizers in highly contaminated PET zones. This can be accomplished by combining enzyme-carrying robots with micro-sorbent release mechanisms to capture hazardous leachates as degradation proceeds.

5.3 Microplastic Filtration and Containment

Micro- and nano-PET particles are now recognized as hazardous due to bioaccumulation and toxicity (oxidative stress, DNA damage, endocrine disruption). Beyond collecting larger PET debris, soft robots have the potential to mitigate microplastic pollution by filtering and containing microscopic PET particles suspended in the water column. These robots can be equipped with fine-mesh filtration systems or electrostatic surfaces that attract and trap microplastics as they move through contaminated areas. Such an approach is crucial for preventing the ingestion of microplastics by marine organisms and reducing their bioaccumulation in the food chain. filtration via soft robots avoids reliance on conventional chemical treatment, which often generates secondary hazardous effluents.

Although not specifically focused on soft robotics, an example study focusing on this application is discussed in (Urso et al, 2023). It was inspired by the potential of intelligent robots as an alternative to traditional water treatment methods, which often fall short in completely removing pollutants or may introduce toxic byproducts into the environment. The authors explored the development and application of self-propelled, programmable micro- and nanoscale robots designed to enhance water monitoring and remediation efforts. These robots are engineered to overcome diffusion-limited reactions, thereby promoting effective interactions with various contaminants, e.g., microplastics, persistent organic pollutants, heavy metals, oils, and pathogenic microorganisms. On the system level, they exhibit capabilities such as autonomous motion, multifunctionality, adaptive responses to environmental stimuli, collective behavior, and inter-robot communication.

Table 5 features a comparison of the capabilities of SR vs. traditional AI technologies.

Table 5 Comparison of Capabilities: Soft Robotics vs. Traditional AI

Capability	Traditional AI (ML/DL/CV)	Soft Robotics
Safe navigation in ecologically sensitive aquatic terrains	N/A	✓
Gentle physical interaction with marine debris and substrates	N/A	✓
Adaptive shape-conforming manipulation	N/A	✓
On-site deployment of enzymes or microbes for biodegradation	N/A	✓
Embodied environmental manipulation (beyond sensing)	N/A	✓
Real-time actuation in dynamic marine conditions	Limited	✓

6 Federated Learning Applications in Marine PET Waste Management

6.1 Collaborative Marine Debris Detection Across Distributed Data Sources

Detecting PET waste in marine environments often requires aggregating data from various sources, such as coastal monitoring stations, research vessels, and satellites. Federated learning enables these disparate entities to collaboratively train machine learning models without sharing raw data, preserving privacy and reducing data transfer overhead. This approach enhances the accuracy of debris detection models by leveraging diverse datasets while maintaining data sovereignty. Moreover, joint training across institutions allows for early detection of high-hazard PET accumulations before fragmentation into micro/nano-plastics, which are particularly hazardous due to bioaccumulation and toxicological effects.

The potential of FL holds for detection tasks and even multi-label classification tasks. Serving as a reference example, we refer the reader to the research proposed in (Ghasemkhani et al, 2024). In this work, the authors proposed a federated multi-label learning framework that allows multiple parties to jointly train classification models without exchanging raw data. The methodology demonstrates high accuracy across various datasets, showcasing its potential for applications like distributed marine debris detection where data privacy is paramount.

6.2 Privacy-Preserving Monitoring of Marine Ecosystems

Monitoring marine ecosystems for PET pollution involves collecting sensitive environmental data. Federated learning facilitates the development of predictive models by allowing institutions to collaboratively analyze data trends without exposing proprietary or sensitive information, e.g., industrial PET waste discharge monitoring, toxic leachate measurements. This ensures compliance with data protection and hazardous materials regulations while enabling comprehensive environmental monitoring.

A pertinent research was proposed in (Zhang et al, 2023a). The authors presented a hierarchical FL architecture designed for Internet of Things (IoT) environments. The framework enables edge devices to perform local training and share model updates with a central server, enhancing data privacy and reducing communication costs. The study's findings are applicable to marine ecosystem monitoring, where distributed sensors can collaboratively detect PET waste without compromising data security.

6.3 Enhancing Marine Waste Management Through Decentralized Learning

Effective management of PET waste in marine environments requires adaptive strategies that can respond to dynamic conditions, which are often challenging to be captured by a single entity. Federated learning supports decentralized model training across various stakeholders, e.g., port authorities and environmental agencies, and regional contexts, e.g., industrial coasts and remote fisheries, enabling dynamic hazard-mapping, real-time updates and localized decision-making. This collaborative approach improves the responsiveness and efficiency of waste management systems.

Although the study presented in (Fu et al, 2023) focused on intelligent transportation systems, it explored an area that can be of a significant importance to marine PET management–the application of federated learning in optimizing resource allocation. The principles outlined can be extended to marine waste management scenarios, facilitating coordinated efforts among different entities to address PET pollution effectively.

6.4 Secure Data Sharing for Marine Pollution Research

Hazard-related PET datasets often contain information about toxic additives, leachates, or microplastic toxicological assays that cannot be freely shared due to biosafety, ethics, or proprietary restrictions. At the same time, collaborative research on marine PET pollution often involves sharing data across institutions with varying data governance policies. Federated learning provides a framework for secure model training without necessitating data centralization, thereby respecting institutional boundaries and fostering collaborative innovation.

The review in (Solis et al, 2024) examines the integration of federated learning with fog computing and blockchain technologies in IoT applications. The study highlights how this combination enhances data security, reduces latency, and supports decentralized decision-making. These insights are pertinent to FL-inspired marine pollution research, where secure and efficient data sharing mechanisms are crucial for collaborative studies on PET waste management.

Table 6 features a comparison of the capabilities of FL vs. traditional AI technologies.

Table 6 Comparison of Capabilities: Federated Learning vs. Traditional AI

Capability	Traditional AI (ML/DL/CV)	Federated Learning (FL)
Collaborative model training across institutions without data sharing	✗	✓
Privacy-preserving learning with decentralized data	✗	✓
Scalable operation under bandwidth and connectivity constraints	✗	✓
Support for multi-modal and non-IID data distributions	Limited	✓
Cross-border environmental modeling with data sovereignty	✗	✓
Localized model personalization with shared global optimization	✗	✓

7 Decision Support Systems Applications in Marine PET Waste Management

7.1 Multi-Criteria Decision Analysis for Sustainable PET Waste Treatment

Selecting the most sustainable PET waste treatment methods in marine environments involves evaluating multiple criteria, including environmental impact, economic feasibility, and social acceptance. Decision Support Systems utilizing Multi-Criteria Decision Analysis (MCDA) frameworks assist policymakers and stakeholders in systematically comparing various treatment options to identify the most balanced and effective solutions. This can involve the computation of hazard severity scores, such as toxicity of degradation byproducts and probability of secondary hazardous emissions. In this sense, DSS could provide policymakers with hazard-weighted treatment hierarchies, elevating safer biodegradation or upcycling pathways over hazardous incineration routes.

The study in (Al-Thani et al, 2022) presented an integrated Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Coefficient of Variation (COV) approach to evaluate the sustainability of eight different PET waste bottle treatment methods. By incorporating environmental, economic, and social criteria, the model aids in identifying the most sustainable treatment option. The findings demonstrate the effectiveness of the integrated approach in supporting decision-making processes for PET waste management in marine contexts.

7.2 Bayesian Belief Networks for Evaluating Plastic Clean-Up Technologies

Implementing plastic clean-up technologies in marine environments requires assessing their effectiveness and potential ecological impacts. Decision Support Systems incorporating Bayesian Belief Networks (BBNs) provide a probabilistic framework to evaluate various clean-up strategies, considering uncertainties and trade-offs between removal efficiency and ecological risks. This is closely related to uncertainty in hazard pathways, e.g., likelihood of PET fragmenting into hazardous microplastics vs. being safely removed. Accordingly, BBNs can help evaluate trade-offs between removal efficiency and the potential release of hazardous leachates during cleanup operations, thereby informing safer technology deployment.

The authors of (Leone et al, 2022) introduced a decision support toolbox that integrates Bayesian Belief Networks to assess plastic clean-up technologies in riverine and estuarine environments. The BBN framework allows for the evaluation of trade-offs between debris removal efficiency and potential adverse effects on aquatic ecosystems. The study highlights the utility of BBNs in informing evidence-based decisions for deploying clean-up interventions in marine settings.

7.3 Systematic Review of Multi-Criteria Decision-Making in Plastic Waste Management

Understanding the application of multi-criteria decision-making methods in plastic waste management provides insights into best practices and areas for improvement. Decision Support Systems benefit from systematic reviews that analyze existing studies, methodologies, and outcomes to enhance decision-making frameworks for managing marine PET waste.

The systematic review proposed in (Santos et al, 2022) covered studies employing multicriteria decision analysis (MCDA) for plastic waste management in marine and terrestrial environments. By examining 20 relevant papers, the review identifies common criteria, decision-making methods, and implementation challenges. The findings offer valuable guidance for developing and refining DSS tools aimed at improving plastic waste management strategies. That being said, most of the existing MCDA reviews underrepresent hazard-specific criteria, such as carcinogenic risk of PET additives, occupational hazards in recycling, or ecotoxicological endpoints. Hence, another research gap lies in integrating hazardous material risk assessment into decision-making frameworks.

7.4 Decision Framework for Estimating the Cost of Marine Plastic Pollution

Quantifying the economic impact of marine plastic pollution is essential for informed policy-making and resource allocation. Particularly, DSS could model the economic burden of hazardous micro/nano-PET accumulation, including long-term costs of ecosystem degradation, healthcare, and food security. Decision Support Systems that incorporate cost estimation frameworks enable stakeholders to assess the financial implications of plastic pollution and prioritize interventions accordingly. This strengthens DSS relevance for risk-informed policy.

In (Murphy et al, 2022), the authors presented a decision framework designed to estimate the economic costs associated with marine plastic pollution. By integrating various cost factors, including environmental damage, clean-up expenses, and economic losses in fisheries and tourism, the framework assists policymakers in understanding the financial burden of plastic pollution.

Table 7 features a comparison of the capabilities of DSS vs. traditional AI technologies.

Table 7 Comparison of Capabilities: Decision Support Systems vs. Traditional AI

Capability	**Traditional AI (ML/DL/CV)**	**Decision Support Systems (DSS)**
Multi-criteria decision-making based on diverse priorities	Limited	✓
Integration of heterogeneous data types (e.g., sensor, policy, economic)	Limited	✓
Simulation of policy and intervention trade-offs	✗	✓
Scenario analysis and long-term strategic planning	Limited	✓
Dynamic adaptation to new data and evolving constraints	Limited	✓

8 Generative AI for Effective Marine PET Management

8.1 Synthetic Data Generation for Improved Detection Models

Developing accurate models for detecting PET waste in marine environments is challenging due to the limited availability of labeled datasets. Generative AI can address this issue by creating synthetic images of PET debris in various underwater conditions, expanding the diversity and volume of training data. Moreover, synthetic datasets can simulate hazardous states of PET (e.g., weathered fragments likely to release leachates, microplastics carrying heavy metals). This approach enhances the robustness of machine learning models, allowing them to more effectively recognize and classify marine plastic waste in real-world scenarios. Furthermore, generative augmentation supports detection models in identifying hazard-critical PET forms — brittle, aged, or chemically altered PET most prone to releasing toxins. To illustrate the effectiveness of generative AI in this application, we review a study that demonstrates its impact on improving underwater debris detection.

A 2022 study (Khindkar and Khindkar, 2022), titled "GAMMA: Generative Augmentation for Attentive Marine Debris Detection", presents a novel solution to the scarcity of labeled underwater waste images. Researchers employed CycleGAN, a generative adversarial network (GAN), to convert terrestrial plastic images into underwater-style images, effectively generating synthetic training datasets. Additionally, the study proposed an attention-based architecture to refine marine debris detection. The results demonstrated that this generative approach significantly outperformed existing detection models, making it a promising tool for enhancing the identification of PET waste by autonomous underwater vehicles (AUVs).

8.2 PET Upcycling with Generative AI

Upcycling PET waste into high-value products such as carbon nanotubes, advanced composites, or novel polymers presents a transformative approach to sustainable waste management. Unlike traditional recycling, which often results in lower-quality materials, PET upcycling leverages Generative AI models, such as Generative Adversarial Networks (GANs), to design and predict new material properties that enhance the structural and functional capabilities of recycled PET. Along the same lines, upcycling design using GenAI can explicitly consider hazard reduction, e.g., designing PET-derived composites that are non-toxic and chemically stable, and minimizing pathways for hazardous byproducts during upcycling (avoiding dioxins or corrosive effluents). By training AI models on extensive polymer databases, researchers can generate optimized molecular structures, enabling the creation of innovative PET-derived materials with extended lifecycles. These advancements contribute to the circular economy, ensuring that PET waste is reutilized in ways that add value rather than degrade its quality.

To highlight a potential research direction in PET upcycling and to reflect on the capabilities mentioned above, we review a pertinent study although it is not focused on PET. In (DE MARTINO et al, 2025), the authors presented a framework that uses physical and qualitative criteria, along with generative AI, to identify new reuse opportunities for textile waste. The generative AI component analyzes data patterns and proposes creative reuse scenarios, considering technical, economic, and sustainability factors. The study's findings suggest that textile waste can be repurposed into high-value applications across various industries.

8.3 Optimizing Biodegradation Processes

So far, we have discussed GenAI's potential in synthesizing datasets and designing new material properties. Along the same lines, GenAI can also assist in designing novel enzymes or microbial strains that efficiently break down PET plastics. By simulating molecular structures and reactions, generative models can predict optimal enzyme-substrate interactions, accelerating the discovery of effective biodegradation pathways.

A pertinent research study was published in (Yip et al, 2024) where they explored an alternative biodegradation approach using engineered microbial communities. The researchers focused on wastewater as a primary pathway for microplastic contamination, demonstrating that tailored microbial consortia could effectively break down PET waste. This study provides evidence that biotechnological interventions could play a key role in addressing marine PET pollution. It is worth noting that GenAI-guided enzyme/microbe design should prioritize hazard minimization by ensuring pathways convert PET into non-toxic metabolites, avoid accumulation of harmful intermediates, and operate under safe conditions that prevent uncontrolled release of hazardous compounds. To demonstrate the role of generative AI in optimizing biodegradation, we review two relevant studies that apply AI-based enzyme engineering.

Table 8 features a comparison of the capabilities of GenAI vs. traditional AI technologies.

Table 8 Comparison of Capabilities: Generative AI vs. Traditional AI

Capability	Traditional AI (ML/DL/CV)	Generative AI (GenAI)
Synthetic data generation for rare or underrepresented scenarios	✗	✓
Enzyme and polymer design through generative modeling	✗	✓
Augmentation of datasets to improve model generalization	Limited	✓
Exploration of hypothetical intervention outcomes	Limited	✓

9 The Applications of Large Multimodal Models in Marine PET Waste Management

9.1 Enhancing Marine Litter Detection through Dataset Augmentation

Along the same lines of the discussion in section 8.1, Large Language Models (LLMs) and Large Multimodal Models (LMMs), when combined with generative models, can augment existing datasets by generating annotated synthetic data, including hazardous PET states (for example, micro/nano-plastics carrying hazardous co-contaminants). Better dataset balance improves the capacity of detection systems to flag high-hazard PET debris rather than just bulk plastic. The research proposed in (Mellone et al, 2025) presented an efficient data augmentation pipeline that combines generative diffusion models (e.g., Stable Diffusion) and LLMs to expand the G-Litter dataset, a marine litter dataset designed for autonomous detection in heterogeneous environments.

9.2 Developing Domain-Specific Vision-Language Models for Marine Environments

General-purpose LLMs often lack the specificity required for marine applications. Developing domain-specific vision-language models enables better understanding and interpretation of marine data, facilitating more effective PET waste management strategies. For instance, marine-specific LMMs can incorporate hazard descriptors — such as “PET fragment with phthalate coating” or “nanoplastic adsorbing cadmium” — so models do not just detect PET but classify hazard severity levels, i.e., hazard-aware classification rather than simple recognition.

In (Zheng et al, 2023), the authors introduced MarineGPT, the first vision-language model specifically designed for the marine domain. By fine-tuning on marine-specific data, MarineGPT demonstrates improved performance in understanding and generating informative responses related to oceanographic content, thereby aiding in public education and marine research initiatives.

9.3 Facilitating Real-Time Monitoring and Optimized Polymer Design for Ocean Waste Management

Capitalizing on the potential of LMMs in analyzing multi-modal data, they can be incoporated to process vast amounts of data from various sources. These sources include satellite imagery, sensor data, and reports from vessels in action, which would support decision-making processes in ocean waste management. One example for this is an LMM that combines, in real-time, chemical sensor data (hazardous leachates), visual imagery (PET debris), and ecological indicators (fish kills, coral bleaching) to prioritize hazard-critical interventions.

Beyond mutlimodal analysis, the generative power of LMMs has stimulated an increasing research attention on the incorporation of those models in generating optimized polymer designs. This can be of a significant benefit in PET management. A pertinent research, although not focused on PET, was proposed in (Yang et al, 2024). The study evaluated the effectiveness of GPT-based and diffusion-based models in generating novel polymer structures. The authors found that their models successfully created new polymer candidates with significantly better characteristics than existing materials in their database. This research demonstrates the potential of LMMs to accelerate the discovery and design of high-performance materials, addressing a key challenge in various sectors including marine waste management.

Table 9 features a comparison of the capabilities of LMMs vs. traditional AI technologies.

10 Explainable Artificial Intelligence Applications in Marine PET Waste Management

10.1 Enhancing Transparency in Marine Plastic Detection Models

In marine environments, detecting PET waste using AI models can be challenging due to the complexity and variability of oceanic conditions. Explainable AI (XAI) techniques provide insights into the decision-making processes of these models, allowing researchers and practitioners to understand, trust, and improve the detection systems. By elucidating how models interpret data, XAI facilitates the refinement of algorithms for more accurate identification of marine plastic debris. Moreover, it helps

Table 9 Comparison of Capabilities: Large Language Models vs. Traditional AI

Capability	**Traditional AI (ML/DL/CV)**	**Large Language Models (LLMs)**
Understanding and synthesizing scientific literature	✗	✓
Enzyme and polymer design through generative modeling	✗	✓
Automated generation of environmental reports and policy drafts	✗	✓
Integration of textual and visual data (via LMMs)	✗	✓
Knowledge-informed scenario simulation and summarization	✗	✓

researchers validate that hazard parameters (e.g., particle size thresholds for nanoplastics, chemical signatures of additives) are driving AI predictions, rather than spurious correlations.

The study in (Kalatzis et al, 2025) presents a new method using explainable AI (XAI) and Raman spectroscopy to classify marine microplastics with high accuracy and transparency. The researchers built a spectral library of plastic and biological samples and tested several machine learning models. They found that certain models, particularly k-Nearest Neighbors (k-NN), were highly effective at identifying microplastics and could also provide insights into their classification logic by highlighting specific chemical bonds in the spectral data. This approach offers a more reliable and understandable tool for environmental monitoring and policy development by moving beyond "black box" AI systems.

10.2 Interpreting AI Predictions in Water Quality Assessment

Assessing water quality in marine ecosystems is vital for understanding the impact of PET waste. AI models can predict various water quality parameters; however, their black-box nature often limits interpretability. Explaiable AI techniques help in deciphering these models, providing clarity on how different factors influence predictions. For instance, XAI can clarify why models flag spikes in hazardous leachates (antimony, bisphenol A, heavy metals) as linked to PET accumulation zones. This transparency aids in validating model outputs and making informed decisions regarding marine environmental management. Along similar lines, it is crucial for regulatory compliance, especially when hazardous material thresholds must be clearly justified for public health reporting. It also

The authors of (Nallakaruppan et al, 2024) introduced an AI-based framework for predicting water quality parameters, incorporating XAI methods to interpret the influence of different variables on the predictions. The model identifies key factors affecting water quality, offering insights into the relationships between pollutants and environmental conditions. The approach enhances the reliability of water quality assessments in marine settings.

10.3 Building Public Trust through Transparent AI Systems

Communities are more likely to engage if they understand the hazard risks being reduced — e.g., a cleanup avoided a certain amount of kilograms of microplastics carrying a specific amount of milligrams of toxic additives. Hence, public engagement and trust are crucial for the success of marine PET waste management initiatives. Towards this goal, transparent AI systems, enabled by XAI, allow the public to understand how decisions are made, fostering trust and acceptance. By demystifying AI processes, XAI can translate complex toxicological AI outputs into language the public understands, reinforcing trust in hazard-mitigation efforts.

A pertinent research was proposed in (Richards et al, 2024). While examining the role of generative AI in supporting nature-based solutions, the authors emphasized that transparency and explainability can enhance public understanding of AI-driven initiatives, thereby increasing trust and engagement. The paper highlights the potential of XAI in promoting community involvement in environmental conservation efforts.

Table 10 features a comparison of the capabilities of XAI vs. traditional AI technologies.

Table 10 Comparison of Capabilities: Explainable AI vs. Traditional AI

Capability	**Traditional AI (ML/DL/CV)**	**Explainable AI (XAI)**
Interpretation of model predictions and decisions	✗	✓
Stakeholder trust and transparency in AI outcomes	✗	✓
Feature-level understanding of model behavior	✗	✓
Regulatory compliance and ecological safety assurance	✗	✓
Interdisciplinary model interpretability (e.g., ecology, policy)	✗	✓
Human-AI collaboration through error diagnosis and feedback	Limited	✓

11 Datasets for Model Training

Datasets form the foundation of AI model training for PET waste management. Public repositories, such as the Plastic Waste Database (PWD), provide diverse datasets that include labeled images, spectroscopic data, and molecular simulations. These datasets enable researchers to train models for tasks such as waste identification, degradation prediction, and upcycling innovation. The availability of such resources has accelerated advancements in AI-based PET management (Listyalina et al, 2022; Lubongo et al, 2024).

11.1 Challenges for Datasets and Models

One of the key challenges in AI applications for PET waste is the standardization of data formats and annotation protocols. This is essential for the interoperability of AI models. Collaborative efforts among academia, industry, and regulatory bodies have led to the development of universal standards for PET waste datasets. These standards ensure consistency and compatibility, facilitating large-scale AI applications in PET waste management and biodegradation.

Another significant challenge is the heterogeneity of waste streams, which can compromise model accuracy. To address this, researchers employ data augmentation techniques and synthetic data generation. GANs, for instance, create diverse training samples that simulate real-world waste compositions, improving the generalizability of AI models. These augmented datasets have been crucial in developing robust models for dynamic and complex recycling scenarios (Goyal and Mahmoud, 2024).

In addition to the well-documented issues of data scarcity, heterogeneity, and standardization in marine PET management, several other dataset-related challenges can undermine the development and deployment of effective AI models. These challenges span both technical and contextual dimensions, influencing not only model accuracy but also fairness, interpretability, and long-term applicability.

Beyond the volume of available datasets, the quality of available data do matter. For, example, noisy labels and annotation errors pose a remarkable challenge towards training effective models. Given the subjective nature of labeling tasks—especially in underwater imagery or microscopic PET fragments—human annotators may introduce inconsistencies or inaccuracies that can mislead models during training. This problem is compounded by class imbalance, where certain types of PET waste (e.g., clear plastic bottles) are far more represented than others (e.g., colored or weathered debris), leading to biased models that generalize poorly across varied marine conditions.

Incomplete or missing data is another common issue, especially in multimodal datasets that rely on satellite imagery, drone footage, or sensor readings. In such cases, corrupted files or absent metadata can limit usable data volume or introduce systematic biases. Similarly, redundancy and duplicate samples—often the result of static monitoring locations or repetitive imagery—can inflate dataset size without increasing informational value, potentially skewing performance metrics or promoting overfitting.

Bias and lack of representativeness present further concerns. Datasets that are geographically skewed or collected in narrowly defined environmental contexts may fail to capture the diversity of marine PET pollution scenarios. This can result in models that perform well in the lab but falter in the field. The problem is exacerbated by high dimensionality and the inclusion of irrelevant or noisy features, particularly in large sensor datasets or fused data modalities, where unfiltered inputs can hinder model convergence or interpretability.

Adding to this complexity is the dynamic nature of marine ecosystems. Ocean currents, temperature, and seasonal variation all contribute to concept drift—shifts in data distribution over time—which can quickly render trained models obsolete if not periodically updated. At the same time, legal, ethical, and institutional barriers may restrict access to high-quality marine data, especially when tied to national monitoring programs, proprietary technologies, or privacy-sensitive sources.

The cost and complexity of data annotation also pose nontrivial barriers. Labeling PET waste in underwater videos, microscopic views, or molecular simulations often demands domain expertise and significant time investment. This bottleneck slows the expansion of labeled datasets and increases the reliance on weak supervision or transfer learning. Multimodal integration introduces additional challenges, as aligning and preprocessing diverse data types—such as combining aerial images with acoustic signals or textual reports—requires careful synchronization to avoid semantic drift or data leakage.

Finally, a critical but often overlooked limitation in the current research landscape is the lack of longitudinal datasets. Most available PET datasets offer spatial snapshots rather than temporal sequences, impeding efforts to build models that capture accumulation trends, degradation timelines, or the long-term effectiveness of cleanup strategies.

Addressing these challenges calls for a combination of strategies, including robust data preprocessing pipelines, synthetic data generation via GANs, semi-supervised learning, and active learning techniques to optimize annotation efforts. As AI continues to be applied to marine PET management, ensuring the quality, diversity, and relevance of training datasets will remain essential for translating algorithmic potential into impactful environmental solutions. Table 11 summarizes the common datset challenges and an example of each challenge in the field of marine PET management.

11.2 Key Datasets for Training

The success of DL models relies heavily on the availability of well-curated datasets. Two significant datasets used in PET waste management are TrashNet and the MODSD dataset (Marine Object and Debris Specific Dataset).

TrashNet is a widely used benchmark dataset for waste classification tasks, consisting of approximately 2,500 labeled images of various waste categories, including plastics, PET, metals, glass, paper, and organic waste. Each image in the dataset is manually labeled, ensuring high annotation quality. The images are captured in controlled environments, which provide clear and consistent visuals, making it an ideal dataset for training foundational AI models for waste sorting.

The primary application of TrashNet is in supervised learning tasks for waste classification. Its compact size and well-organized labels make it accessible for researchers and practitioners to train and test machine learning models efficiently. Additionally, TrashNet has been instrumental in developing lightweight AI models for real-time waste segregation systems. The dataset's versatility is reflected in its use across various applications, from small-scale recycling robots to larger automated waste management facilities. Despite its strengths, TrashNet's controlled image collection environment limits its diversity compared to more expansive datasets. However, it remains a critical resource for initiating research and building baseline models in waste classification (Aral et al, 2018).

Table 11 Common Dataset Challenges and Their Relevance to Marine PET Management

Challenge	Example in Marine PET Management
Scarcity	Limited labeled datasets of PET waste in underwater drone footage.
Heterogeneity	Mixed plastic types (e.g., PET, HDPE) often appear together in marine debris samples.
Label Noise and Annotation Errors	Annotators confuse PET fragments with PET-like materials such as nylon or bio-plastics.
Class Imbalance	Majority of images contain non-PET debris; PET-specific examples are underrepresented.
Missing Data	Data gaps from satellite or buoy sensors due to weather or technical issues.
Redundancy and Duplicates	Multiple images or samples of the same PET bottle across time and location.
Bias and Lack of Representativeness	Datasets mainly collected near coastal cleanup sites, underrepresenting deep-sea PET occurrences.
High Dimensionality and Irrelevant Features	Satellite images may contain irrelevant spectral bands unrelated to plastic detection.
Dynamic or Evolving Data Distributions	Seasonal changes in PET waste accumulation due to ocean current shifts or tourism cycles.
Data Privacy and Access Restrictions	Access to commercial satellite imagery for marine monitoring is often restricted or costly.
Annotation Cost and Complexity	Requires domain experts to annotate microplastics in sediment or biological tissue samples.
Multimodal Integration Challenges	Difficulty in synchronizing PET data from satellite images, sonar scans, and physical water samples.

The SeaClear Marine Debris Dataset is a public, shallow-water underwater vision benchmark designed for object detection and instance segmentation of marine debris. It contains 8,610 ROV-captured images collected with different cameras across multiple Mediterranean sites in Croatia (Bistrina, Jakljan, Lokrum, Slano) and France (Marseille). Each image is annotated into 40 object classes spanning three principal categories: debris, marine life, and robot parts—so models can learn to distinguish litter from background biota and vehicle components under realistic turbidity and lighting. The dataset is straightforward to access and cite for benchmarking underwater trash detection and segmentation methods (Duras et al, 2024b).

The TACO (Trash Annotations in Context) (Proença and Simões, 2020; Proença and Simões, 2024) is an open, crowd-sourced dataset for litter detection and instance segmentation, containing photos of waste across diverse environments (streets, parks, beaches) with pixel-wise masks and a hierarchical class taxonomy in COCO format; images are hosted on Flickr and continually expanded through community contributions and annotation tools provided by the project. It is commonly used to train and benchmark object detection/segmentation models on 60+ fine-grained litter categories (e.g., PET bottles).

The OpenLitterMap is an open, citizen-science geospatial database that crowd-sources smartphone photos of litter, pairs them with user-generated labels (e.g., material, brand), and publishes the geotagged records under an open data model suitable for analysis and model training; the platform also experiments with a blockchain-based incentive ("Littercoin") to encourage sustained contributions and data quality. Public access to the live map, dataset downloads, and API-based retrieval is provided via the official site and tools (e.g., a QGIS plugin), and the project's aims and incentive mechanism are documented in the peer-reviewed literature (OpenLitterMap, 2024; Lynch, 2018).

MARIDA (Marine Debris Archive) (Kikaki et al, 2022) is an open-access benchmark built from multispectral Sentinel-2 imagery to support weakly supervised pixel-level semantic segmentation and related classification tasks for floating marine debris in the presence of confounding sea features (e.g., wakes, foam, Sargassum, ships, turbid/clear water, clouds). The dataset provides georeferenced annotations derived from verified debris events across diverse regions and conditions, along with baseline learning protocols and spectral analyses reported in its data descriptor. Public distribution (with documentation and code for reproducing baselines) is maintained via a project site (Marine Debris Archive, 2025), and subsequent studies have used MARIDA to evaluate spectral indices and debris mapping approaches, underscoring its role as a reference dataset for satellite-based debris detection.

PoTATO (Batista et al, 2024) is a recent open dataset tailored to afloat-trash detection that augments conventional RGB imagery with raw polarimetric measurements to mitigate sun-glint and lighting variability on water surfaces. Curated for robotic cleanup and environmental monitoring scenarios, it focuses on plastic bottles and reports 12,380 labeled instances, enabling analyses of when and how polarization improves object detection over standard vision alone. The dataset release provides data, code, and experimental baselines, and explicitly documents the conditions under which polarization yields gains, making it a strong complement to beach/underwater litter sets that lack polarization cues.

12 Discussion

12.1 Integration of AI Technologies

The preceding sections demonstrate that individual AI technologies—such as reinforcement learning (RL), generative AI (GenAI), edge AI, soft robotics, federated learning (FL), decision support systems (DSS), large language models (LLMs), and explainable AI (XAI)—offer unique capabilities for addressing specific challenges in marine PET management including streams classified as hazardous due to chemical contamination, adsorbed POPs/metals, or pathogen load. However, their combined deployment holds even greater potential for enabling intelligent, scalable, and adaptive interventions that meet HAZMAT risk thresholds and chain-of-custody requirements. Based on the insights presented in Sections 3–10, Table 13 maps distinctive capability clusters to their enabling AI paradigms, and the remainder of this section elaborates on these synergies.

Table 12 Overview of Datasets for PET Waste Management and AI Applications (Aral et al, 2018; Duras et al, 2024b,a; Lynch, 2018; OpenLitterMap, 2024; Proença and Simões, 2020; Proença and Simões, 2024; Kikaki et al, 2022; Marine Debris Archive, 2025; Batista et al, 2024)

Dataset	Dataset Size	Diversity	Labeling Quality	Primary Application	Advantages
TrashNet	~2,500 images	Focuses on common waste categories like plastics, metals, paper, and PET.	Manually labeled; high accuracy.	Training supervised learning models for waste classification.	Compact and well-labeled dataset ideal for foundational AI model development.
SeaClear Marine Debris Dataset	8,610 images	High (multi-location, multi-camera underwater footage)	COCO-format JSON annotations for 40 object categories	Object detection and segmentation of underwater marine debris	Location diversity; includes robot parts, marine life, and debris with benchmarking support
TACO (Trash Annotations in Context)	~1,500 images (4,784 annotations)	High (wooded, urban, beach)	Manual COCO-format annotations with taxonomy	Object detection and segmentation in diverse real-world scenarios	Open-source; well-suited for waste detection in natural settings
OpenLitterMap	~8,200 geotagged images	High (global, citizen-generated)	Human-verified annotations with metadata (brand, material)	Geospatial PET tracking and citizen science engagement	Publicly available; blockchain-supported incentives; rich metadata
MARIDA (Marine Debris Archive)	1,381 image patches (256×256 px)	High (15 annotated sea-surface classes across global sites)	Pixel-level annotations with graded confidence (high/moderate/low)	Semantic segmentation and multi-label classification of marine debris in satellite imagery	Globally distributed benchmark using Sentinel-2 data; includes co-occurring oceanic and atmospheric features
PoTATO	~12,380 labeled plastic-bottle instances	High (multiple outdoor water scenes; varied sun–glint/illumination; viewpoints)	Bounding-box annotations for bottles; consistent protocol; includes raw polarization channels	Afloat-trash detection on water surfaces; analysis of polarization benefits for robust detection	Polarimetric cues mitigate glare/reflections; public dataset with code and baselines

A key synergy arises from the integration of edge AI with RL and soft robotics, enabling autonomous marine agents to perform real-time decision-making, waste collection, and enzyme deployment in dynamic aquatic environments. For hazardous PET, embed on-board hazard screening (e.g., VOC/PAH sensors, conductivity/pH for leachates), rule-based "do-not-touch" policies, and automatic containment actions (sorbent release, micro-booms) before grasp/ingestion. For instance, soft robots equipped with edge-based RL models can learn optimal navigation paths while responding to changing ocean currents and debris distributions while enforcing exclusion zones around suspected hazardous patches and logging exposures for decontamination workflows.

Another promising intersection is between FL and decision support systems. Federated learning provides privacy-preserving, decentralized model training across geographically distributed marine monitoring stations, while DSS frameworks offer a structured interface to assimilate these distributed insights into multi-criteria policy and intervention decisions. For example, federate incident data from ports/response vessels to update risk maps without sharing sensitive locations; in the DSS, add HAZMAT-specific criteria—toxicity class, persistence, bioaccumulation, IMDG/ADR compatibility—to prioritize containment, routing, PPE, and staging. Integrating the two would enable near real-time policy refinement based on locally updated models without breaching data sovereignty constraints.

Generative AI and LMMs, on the other hand, can jointly address both the data scarcity and knowledge synthesis challenges. While GenAI enhances detection and modeling capabilities through synthetic data generation and simulation, LMMs can be used to synthesize cross-modal data—including sensor readings, remote sensing imagery, and textual reports—into actionable insights. GenAI can also be used to create rare "worst-case" hazard scenarios (e.g., contaminated PET rafts, storm-mobilized stockpiles) and LMMs to draft Incident Command Systems(ICS)-ready playbooks, public risk messages, and transport manifests with hazard labels. Their combined use could also support automated reporting, scenario generation, and community-focused science communication, especially when tailored using explainable AI techniques.

Finally, XAI serves as a unifying layer across all AI technologies by enhancing transparency, interpretability, and stakeholder trust. Whether in regulatory environments, community engagement, or ecological safety assessments, the ability to explain model decisions becomes essential for the widespread adoption of AI-driven systems. This also supports compliance audits and post-incident reviews. Thus, a holistic integration framework—grounded in explainability and modular interoperability—can bridge isolated advancements into cohesive, multi-agent systems for intelligent marine PET management with embedded hazard identification, classification, and response primitives throughout the pipeline.

12.2 Adoption Barriers and Ethical and Practical Considerations

The practical implementation of emerging AI technologies in marine PET management is not solely a matter of technical readiness but also deeply intertwined with ethical, institutional, and contextual considerations. Adoption barriers, in particular, represent

Table 13 Matrix of AI Capabilities and Their Enabling AI Paradigms

Capability Cluster	DSS	Edge AI	Federated Learning	GenAI	LLMs	RL	Soft Robotics	XAI
Real-time & adaptive decision-making								
Decentralized operation & collaboration								
Autonomous action in dynamic environments								
Privacy-preserving, distributed learning								
Simulation and scenario modeling								
Human-AI collaboration & trust-building								
Policy design and interpretation								
Synthetic data generation & augmentation								
Scientific or enzymatic innovation								
Environmental sensing + actuation								

Legend:

Relationship exists between Capability and Paradigm.

No direct relationship noted.

a critical subset of these broader concerns, often arising from limitations in infrastructure, stakeholder trust, policy alignment, and data governance. Understanding these barriers through an ethical and practical lens is essential for guiding responsible AI integration in environmental sustainability contexts and for ensuring that hazardous exposures linked to PET-derived micro/nanoplastics and toxic degradation products are not exacerbated by technological shortcomings.

A foremost practical challenge is the fragmented infrastructure across coastal and marine monitoring agencies, which hinders the deployment of AI systems requiring real-time data input, model retraining, or distributed computing. For example, federated learning and edge AI systems depend on consistent device interoperability, secure communication protocols, and local processing capacity—requirements often unmet in under-resourced marine regions. In the context of hazardous PET waste, these infrastructure gaps risk delaying early warnings of toxic hotspots or hazardous leachate flows, directly endangering human and ecological health. Economic feasibility also poses a barrier, especially when transitioning from traditional monitoring tools to high-cost autonomous robots, drones, or smart sensors. This raises environmental justice concerns, as resource-constrained regions may remain disproportionately exposed to hazardous PET accumulation without access to protective AI tools.

Ethically, data privacy and ownership remain major hurdles. Collaborative approaches like federated learning and large multimodal models rely on cross-institutional data flows, yet many stakeholders lack formal mechanisms to ensure data sovereignty, anonymization, or equitable access. These concerns are amplified in international marine zones, where jurisdictional ambiguities further complicate collaboration. Hazard classification and reporting data—such as concentrations of PET-associated endocrine disruptors or carcinogenic residues—carry high stakes; if mishandled, they can undermine trust, delay emergency responses, and even expose local populations to unacknowledged risks.

Trust and explainability represent another layer of adoption resistance. Black-box models, especially deep learning-based systems used in waste detection or biodegradation prediction, may not gain regulatory approval or stakeholder confidence without explainable outputs. Here, the integration of explainable AI (XAI) becomes both a technical requirement and an ethical imperative—one that supports transparency, accountability, and informed decision-making. In hazardous waste contexts, explainability is essential for auditing whether AI-driven recommendations meet safety thresholds for handling, transport, and disposal of PET debris classified as hazardous.

From a practical standpoint, standardization gaps—in data formats, sensor integration, and model validation—impede the scaling of AI systems across regions. The absence of universally accepted protocols for annotating marine PET datasets, for example, undermines transferability and limits cross-project synergy. This is especially problematic when datasets track hazard-specific attributes (e.g., toxicity levels, persistence indices, bioaccumulation factors); lack of standards can prevent regulators from accurately comparing risks across regions.

Finally, social and behavioral factors must be acknowledged. Public perception of AI in marine conservation is shaped by cultural values, environmental awareness, and historical mistrust in technology-driven governance. Thus, ethical AI adoption must include efforts in public engagement, co-design with local communities, and transparent policy frameworks that account for environmental justice and long-term sustainability. In hazard scenarios, failure to communicate clearly about toxic risks from PET waste can fuel public mistrust, resistance to interventions, or unsafe self-cleanup practices that heighten exposure.

In sum, the adoption of AI in marine PET management is shaped by a constellation of technical, ethical, and logistical considerations. Viewing adoption barriers as expressions of deeper practical and ethical challenges enables more holistic planning for future AI deployments—ensuring they are not only effective but also equitable, transparent, and socially legitimate while explicitly minimizing hazardous-material risks associated with PET persistence, toxic degradation products, and human/ecosystem exposure pathways

12.3 Future Directions

Building on the insights, synergies, and barriers identified across this review, several future research and deployment trajectories can further elevate the role of AI in marine PET management particularly when PET is framed not just as waste, but as a hazardous material with toxicological and ecotoxicological implications.

One foundational direction is the pursuit of transdisciplinary integration, involving collaboration between AI researchers, marine ecologists, robotic engineers, and policy stakeholders. Such integration is necessary to ensure that technological interventions align with ecological dynamics and community values. This need is particularly apparent in areas like autonomous marine waste collection (Section 3.2), enzyme deployment via robotics (Section 5.2), and policy optimization through RL and DSS (Sections 3.4 and 7.1). In each of these domains, hazard considerations—such as handling of PET fragments carrying adsorbed heavy metals, persistent organic pollutants, or endocrine-disrupting additives—must be explicitly incorporated into design and evaluation.

Another priority is the development of benchmarking and validation frameworks to assess AI model performance across tasks such as detection, classification, biodegradation, and policy support. The current absence of standard evaluation criteria (highlighted in Section 11.1) and the fragmented nature of existing datasets (Section 11.2) hinder comparability and reproducibility. Establishing shared benchmarks tailored to marine environments would enhance rigor and model portability. Benchmarks should also include hazard-related metrics: toxicity thresholds, persistence indices, and exposure pathways, ensuring that AI systems are evaluated not only for technical accuracy but also for their ability to reduce hazardous risks.

Exploring hybrid AI architectures represents a promising avenue. For instance, combining federated learning with decision support systems (Sections 6 and 7), or reinforcement learning with edge-enabled soft robotics (Sections 3, 4, and 5), could yield systems that are not only adaptive but also scalable and context-aware. Section 12.1 already outlined the conceptual merit of such integrations, and emerging paradigms like neuromorphic computing and self-organizing agents may further strengthen these hybrid pipelines. Such hybrid systems could, for example, fuse hazard classification data with real-time robotic actions, ensuring containment protocols are automatically triggered when PET debris with toxic coatings or hazardous degradation products is encountered.

Efforts should also target the expansion of marine-specific datasets, particularly longitudinal, multimodal, and geographically diverse ones. Sections 11.1 and 11.2 emphasize how data scarcity, class imbalance, and limited representativeness constrain model development. Collaborative open-data initiatives and citizen science contributions (referenced in Section 9.4 and Table 12) could help bridge this gap. Here, hazard-oriented annotation—flagging toxicity classes, bioaccumulation risks, and leachate profiles of PET waste—would make datasets more directly useful for hazardous-materials management.

Addressing regulatory and ethical readiness is equally critical. The limitations noted in Section 12.2—such as data privacy, interoperability barriers, and the lack of explainable outputs—highlight the importance of designing AI systems that are ethically robust and compliant with data governance policies. Explainable AI, discussed in Section 10, should serve as a foundational layer in future AI toolchains to ensure transparency and stakeholder trust. In hazard-sensitive deployments, explainability also underpins compliance with hazardous waste transport regulations, occupational safety standards, and international conventions on marine pollution.

The augmentation of public engagement and policy participation through AI also offers great promise. Interactive platforms powered by LMMs and explainable dashboards can facilitate real-time feedback between communities and marine management authorities.

Ultimately, the field should work toward a closed-loop marine PET management ecosystem, where AI tools are orchestrated across the full lifecycle: from detection and collection (Sections 3, 4, 5) to degradation and upcycling (Sections 3.3, 5.2, 8.2, 8.4), to policy modeling and public engagement (Sections 7, 9, 10). This end-to-end vision integrates data, models, and human expertise into a coherent system capable of adapting to the evolving realities of marine pollution and sustainability imperatives.

Supplementary Material.

1. Article records for generating the co-occurrence map using VOSviewer, for both WoS and Copus, can be found through the following link: https://1drv.ms/f/c/19faffbe78315469/Ej8VT2ww5h9Hp3SFw0kawM0BWjr76OEZzjEW7nQgqHI9JQ?e=8RutHr
2. The JSON files representing the co-occurrence maps generated by VOSviewer for WoS and Scopus can be found through the following link: https://1drv.ms/f/c/19faffbe78315469/EvkqRowsfhVHpghvtAUqSuMBKZgmMVpMSyFsuM4eqZyyUw?e=vavKL4

References

Adam, Issahaku and Walker, Tony R and Bezerra, Joana Carlos and Clayton, Andrea (2020) Policies to reduce single-use plastic marine pollution in west africa. Marine Policy 116:103928

Ahmaditabatabaei, Seyedehazita and Kyazze, Godfrey and Iqbal, Hafiz MN and Keshavarz, Tajalli (2021) Fungal enzymes as catalytic tools for polyethylene terephthalate (pet) degradation. Journal of Fungi 7(11):931

Ahmed, Temoor and Shahid, Muhammad and Azeem, Farrukh and Rasul, Ijaz and Shah, Asad and Noman, Muhammad and Hameed, Amir and Manzoor, Natasha and Manzoor, Irfan and Muhammad, Sher (2018) Biodegradation of plastics: current scenario and future prospects for environmental safety. Environmental Science and Pollution Research 25:1–12. https://doi.org/10.1007/s11356-018-1234-9

Muhammad Aitzaz Akram and Rangasamy Savitha and Gemma K. Kinsella and Kieran Nolan and Barry J. Ryan and Gary T. Henehan (2024) Microbial and enzymatic biodegradation of plastic waste for a circular economy. Applied Sciences 14(24):11942. https://doi.org/10.3390/app142411942

Al-Thani, Nayla Ahmad and Al-Ansari, Tareq and Haouari, Mohamed (2022) Integrated topsis-cov approach for selecting a sustainable pet waste management technology: A case study in qatar. Heliyon 8(8)

Ali, Sameh S and Elsamahy, Tamer and Al-Tohamy, Rania and Zhu, Daochen and Mahmoud, Yehia A-G and Koutra, Eleni and Metwally, Metwally A and Kornaros, Michael and Sun, Jianzhong (2021) Plastic wastes biodegradation: Mechanisms, challenges and future prospects. Science of The Total Environment 780:146590

Almroth, Bethanie Carney and Eggert, Håkan (2020) Marine plastic pollution: Sources, impacts, and policy issues. Review of Environmental Economics and Policy 14(3):317–326. https://doi.org/10.1093/reep/rez012, URL https://www.journals.uchicago.edu/doi/10.1093/reep/rez012

Alnuaimi, Eiman and Alsafi, Mariam and Alshehhi, Maitha and Debe, Mazin and Salah, Khaled and Yaqoob, Ibrar and Zemerly, M Jamal and Jayaraman, Raja (2023) Blockchain-based system for tracking and rewarding recyclable plastic waste. Peer-to-Peer Networking and Applications 16(1):328–346

Rahmi Arda Aral and Seref Recep Keskin and Mahmut Kaya and Murat Haciomeroglu (2018) Classification of trashnet dataset based on deep learning models. 2018 IEEE International Conference on Big Data (Big Data) pp 2058–2062. https://doi.org/10.1109/bigdata.2018.8622212

Audrézet, François and Zaiko, Anastasija and Lear, Gavin and Wood, Susanna A and Tremblay, Louis A and Pochon, Xavier (2021) Biosecurity implications of drifting marine plastic debris: current knowledge and future research. Marine Pollution Bulletin 162:111835

Baskerville, Richard L and Myers, Michael D and Yoo, Youngjin (2019) Digital first: The ontological reversal and new challenges for is research. MIS Quarterly: Management Information Systems

Batista, Luis FW and Khazem, Salim and Adibi, Mehran and Hutchinson, Seth and Pradalier, Cedric (2024) In: , Springer, pp 190–205

Booth, Henry and Ma, Wanli and Karakuş, Oktay (2023) High-precision density mapping of marine debris and floating plastics via satellite imagery. Scientific reports 13(1):6822

Bułkowska, Katarzyna and Zielińska, Magdalena and Bułkowski, Maciej (2024) Blockchain-based management of recyclable plastic waste. Energies 17(12):2937

Tianhao Cheng and Daiki Kojima and Hao Hu and Hiroshi Onoda and Andante Hadi Pandyaswargo (2024) Optimizing waste sorting for sustainability: An ai-powered robotic solution for beverage container recycling. Sustainability 16(23):10155. https://doi.org/10.3390/su162310155

Danilov, Aleksandr and Serdiukova, Elizaveta (2024) Review of methods for automatic plastic detection in water areas using satellite images and machine learning. Sensors 24(16):5089

Danso, Dominik and Chow, Jennifer and Streit, Wolfgang R (2019) Plastics: environmental and biotechnological perspectives on microbial degradation. Applied and environmental microbiology 85(19):e01095–19

DE MARTINO, Giovanni and LEONE, Rosa and BUCCI, Marica and Dassisti, Michele (2025) A decisional framework for second-life applications of textile waste: A data-driven and generative ai approach. Materials Research Proceedings 57

Derraik, José GB (2002) The pollution of the marine environment by plastic debris: a review. Marine pollution bulletin 44(9):842–852

Din, Salah Ud and Kalsoom and Satti, Sadia Mehmood and Uddin, Salah and Mankar, Smita V and Ceylan, Esma and Hasan, Fariha and Khan, Samiullah and Badshah, Malik and Beldüz, Ali Osman and others (2023) The purification and characterization of a cutinase-like enzyme with activity on polyethylene terephthalate (pet) from a newly isolated bacterium stenotrophomonas maltophilia prs8 at a mesophilic temperature. Applied Sciences 13(6):3686

Ellen M. Ditria and Christina A. Buelow and Manuel Gonzalez-Rivero and Rod M. Connolly (2022a) Artificial intelligence and automated monitoring for assisting conservation of marine ecosystems: A perspective. Frontiers in Marine Science 9. https://doi.org/10.3389/fmars.2022.918104

Ditria, Ellen M. and Lopez-Marcano, Sebastian and Sievers, Michael and Jinks, Elizabeth L. and Brown, Christopher J. and Connolly, Rod M. (2022b) Artificial intelligence and automated monitoring for assisting conservation of marine ecosystems: A perspective. Frontiers in Marine Science 9:918104. https://doi.org/10.3389/fmars.2022.918104, URL https://www.frontiersin.org/articles/10.3389/fmars.2022.

918104/full

Duras, Antonio and Wolf, Benjamin J. and Ilioudi, Athina and Palunko, Ivana and De Schutter, Bart (2024a) A dataset for detection and segmentation of underwater marine debris in shallow waters. https://data.4tu.nl/datasets/4f1dff25-e157-4399-a5d4-478055461689, 4TU.ResearchData. Accessed May 9, 2025

Antun Duras and Ben J. Wolf and Athina Ilioudi and Ivana Palunko and Bart De Schutter (2024b) A dataset for detection and segmentation of underwater marine debris in shallow waters. Scientific Data 11(1). https://doi.org/10.1038/s41597-024-03759-2

Esmaeili Nasrabadi, Afsaneh and Ramavandi, Bahman and Bonyadi, Ziaeddin (2023) Recent progress in biodegradation of microplastics by aspergillus sp. in aquatic environments. Colloid and Interface Science Communications 57:100754. https://doi.org/10.1016/j.colcom.2023.100754

Plastics Europe (2022) Plastics - the Facts 2022 • Plastics Europe — plasticseurope.org. https://plasticseurope.org/knowledge-hub/plastics-the-facts-2022/, [Accessed 17-09-2024]

Fakirov, Stoyko (2017) Fundamentals of polymer science for engineers. John Wiley & Sons

Gabriel Ferreira and Rafael Godoy Cerqueira and Christiane Kleinke and Fernanda de Souza Ferreira and Edson Luiz Durigon and Carla Cristina Dos Santos and Ana Paula Guimarães (2023) Multidomain chimeric enzymes as a promising alternative for biocatalysis. Frontiers in Microbiology 14:1092786. https://doi.org/10.3389/fmicb.2023.1092786, URL https://www.frontiersin.org/articles/10.3389/fmicb.2023.1092786

Fu, Xiuhua and Peng, Rongqun and Yuan, Wenhao and Ding, Tian and Zhang, Zhe and Yu, Peng and Kadoch, Michel (2023) Federated learning-based resource management with blockchain trust assurance in smart iot. Electronics 12(4):1034

Gambarini, Victor and Pantos, Olga and Kingsbury, Joanne M and Weaver, Louise and Handley, Kim M and Lear, Gavin (2021) Phylogenetic distribution of plastic-degrading microorganisms. Msystems 6(1):10–1128

Gao, Rui and Pan, Haojie and Kai, Lei and Han, Kun and Lian, Jiazhang (2022) Microbial degradation and valorization of poly (ethylene terephthalate)(pet) monomers. World Journal of Microbiology and Biotechnology 38(5):89

Gelfand, Natalia and Orel, Vojtech and Cui, Wenqiang and Damborsky, Jiri and Li, Chenglong and Prokop, Zbynek and Xie, Wen Jun and Warshel, Arieh (2025) Biochemical and computational characterization of haloalkane dehalogenase variants designed by generative ai: Accelerating the sn2 step. Journal of the American

Chemical Society

Ghasemkhani, Bita and Varliklar, Ozlem and Dogan, Yunus and Utku, Semih and Birant, Kokten Ulas and Birant, Derya (2024) Federated multi-label learning (fmll): Innovative method for classification tasks in animal science. Animals 14(14):2021

Mandeep Goyal and Qusay H. Mahmoud (2024) A systematic review of synthetic data generation techniques using generative ai. Electronics 13(17):3509. https://doi.org/10.3390/electronics13173509

Graf, Leonie G and Michels, Emil AP and Yew, Yelwin and Liu, Weidong and Palm, Gottfried J and Weber, Gert (2021) In: , vol 648. Elsevier, p 337–356

Gray, Austin D and Weinstein, John E (2017) Size-and shape-dependent effects of microplastic particles on adult daggerblade grass shrimp (palaemonetes pugio). Environmental toxicology and chemistry 36(11):3074–3080

Gugliandolo, Giovanni and Quattrocchi, Antonino and Latino, Mariangela and Aloisio, Davide and Crupi, Giovanni and Donato, Nicola (2024) Microplastic identification in marine environments: A low-cost and effective approach based on transmitted light measurements. Acta IMEKO 13(2):1–8

Guo, Pengwei and Wang, Yuhuan and Moghaddamfard, Parastoo and Meng, Weina and Wu, Shenghua and Bao, Yi (2024) Artificial intelligence-empowered collection and characterization of microplastics: A review. Journal of Hazardous Materials p 134405

Jambeck, Jenna R and Geyer, Roland and Wilcox, Chris and Siegler, Theodore R and Perryman, Miriam and Andrady, Anthony and Narayan, Ramani and Law, Kara Lavender (2015) Plastic waste inputs from land into the ocean. science 347(6223):768–771

Jiang, Wankui and Sun, Jingxiang and Dong, Weiliang and Zhou, Jie and Jiang, Yujia and Zhang, Wenming and Xin, Fengxue and Jiang, Min (2023) Characterization of a novel esterase and construction of a rhodococcus-burkholderia consortium capable of catabolism bis (2-hydroxyethyl) terephthalate. Environmental Research 238:117240

Jin Jin and Jane Arciszewski and Karine Auclair and Zongchao Jia (2023) Enzymatic polyethylene biorecycling: Confronting challenges and shaping the future. Journal of Hazardous Materials 460:132449. https://doi.org/10.1016/j.jhazmat.2023.132449

Kalatzis, Dimitris and Katsafadou, Angeliki I and Katsarou, Eleni I and Chatzopoulos, Dimitrios C and Kiouvrekis, Yiannis (2025) Explainable artificial intelligence for the rapid identification and characterization of ocean microplastics. Microplastics 4(3):51

Kamishima, Yuko and Gremmen, Bart and Akizawa, Hikari (2018) Can merging a capability approach with effectual processes help us define a permissible action range for ai robotics entrepreneurship? Philosophy of Management 17(1):97–113

Karthik, R and Robin, RS and Purvaja, R and Ganguly, D and Anandavelu, I and Raghuraman, R and Hariharan, G and Ramakrishna, A and Ramesh, R (2018) Microplastics along the beaches of southeast coast of india. Science of the Total Environment 645:1388–1399

Kawai, Fusako and Kawabata, Takeshi and Oda, Masayuki (2019) Current knowledge on enzymatic pet degradation and its possible application to waste stream management and other fields. Applied microbiology and biotechnology 103:4253–4268

Khairul Anuar, Nurul Fatin Syamimi and Huyop, Fahrul and Ur-Rehman, Ghani and Abdullah, Faizuan and Normi, Yahaya M and Sabullah, Mohd Khalizan and Abdul Wahab, Roswanira (2022) An overview into polyethylene terephthalate (pet) hydrolases and efforts in tailoring enzymes for improved plastic degradation. International journal of molecular sciences 23(20):12644

Khindkar, Vaishnavi and Khindkar, Janhavi (2022) Gamma: Generative augmentation for attentive marine debris detection. arXiv preprint arXiv:221203759

Khriss, Abdelaadim and Elmiad, Aissa Kerkour and Badaoui, Mohammed and Barkaoui, Alae-eddine and Zarhloule, Yassine (2024) Advances in machine learning and deep learning approaches for plastic litter detection in marine environments. Journal of Theoretical and Applied Information Technology 102(5):1885–1895. URL https://www.jatit.org/volumes/Vol102No5/18Vol102No5.pdf

Katerina Kikaki and Ioannis Kakogeorgiou and Paraskevi Mikeli and Dionysios E. Raitsos and Konstantinos Karantzalos (2022) Marida: A benchmark for marine debris detection from sentinel-2 remote sensing data. PLOS ONE 17(1):e0262247. https://doi.org/10.1371/journal.pone.0262247, URL https://doi.org/10.1371/journal.pone.0262247

Kim, Jong-Hoon and Lee, So-Hye and Lee, Byeong-Min and Son, Kwang-Hee and Park, Ho-Yong (2023) Biodegradation potential of polyethylene terephthalate by the two insect gut symbionts xanthomonas sp. hy-74 and bacillus sp. hy-75. Polymers 15(17):3546

Kowsari, Elaheh and Ramakrishna, Seeram and Gheibi, Mohammad and Chinnappan, Amutha and others (2023) Marine plastics, circular economy, and artificial intelligence: A comprehensive review of challenges, solutions, and policies. Journal of Environmental Management 345:118591

Alexander Kroll and Sahasra Ranjan and Martin K. M. Engqvist and Martin J. Lercher (2023) A general model to predict small molecule substrates of enzymes based on machine and deep learning. Nature Communications 14(1). https://doi.

org/10.1038/s41467-023-38347-2

Kunwar, Suman and Owabumoye, Banji Raphael and Alade, Abayomi Simeon (2025) Plastic waste detection using deep learning: Insights from the wadaba dataset. Industrial and Domestic Waste Management 5(1):1–11

Kushwaha, Anamika and Goswami, Lalit and Singhvi, Mamata and Kim, Beom Soo (2023) Biodegradation of poly (ethylene terephthalate): mechanistic insights, advances, and future innovative strategies. Chemical Engineering Journal 457:141230

Leone, Giulia and Catarino, Ana I and Pauwels, Ine and Mani, Thomas and Tishler, Michelle and Egger, Matthias and Forio, Marie Anne Eurie and Goethals, Peter LM and Everaert, Gert (2022) Integrating bayesian belief networks in a toolbox for decision support on plastic clean-up technologies in rivers and estuaries. Environmental Pollution 296:118721

Latifah Listyalina and Yudianingsih Yudianingsih and Adjie Wibowo Soedjono and Evrita Lusiana Utari and Dhimas Arief Dharmawan (2022) Deep-ric: Plastic waste classification using deep learning and resin identification codes (ric). Telematika 19(2):215. https://doi.org/10.31315/telematika.v19i2.7419

Löhr, Ansje and Savelli, Heidi and Beunen, Raoul and Kalz, Marco and Ragas, Ad and Van Belleghem, Frank (2017) Solutions for global marine litter pollution. Current opinion in environmental sustainability 28:90–99

Lu, Hongyuan and Diaz, Daniel J and Czarnecki, Natalie J and Zhu, Congzhi and Kim, Wantae and Shroff, Raghav and Acosta, Daniel J and Alexander, Bradley R and Cole, Hannah O and Zhang, Yan and others (2022) Machine learning-aided engineering of hydrolases for pet depolymerization. Nature 604(7907):662–667

Cesar Lubongo and Mohammed A. A. Bin Daej and Paschalis Alexandridis (2024) Recent developments in technology for sorting plastic for recycling: The emergence of artificial intelligence and the rise of the robots. Recycling 9(4):59. https://doi.org/10.3390/recycling9040059

Seán Lynch (2018) Openlittermap.com – open data on plastic pollution with blockchain rewards (littercoin). https://www.researchgate.net/publication/325696249, researchGate. Accessed May 9, 2025

Maheswaran, Baskaran and Al-Ansari, Mysoon and Al-Humaid, Latifah and Raj, Joseph Sebastin and Kim, Woong and Karmegam, Natchimuthu and Rafi, Kasim Mohamed (2023) In vivo degradation of polyethylene terephthalate using microbial isolates from plastic polluted environment. Chemosphere 310:136757

Malafatti-Picca, Lusiane and Bucioli, Elaine Cristina and de Barros Chaves, Michel Ricardo and de Castro, Aline Machado and Valoni, Érika and de Oliveira, Valéria

Maia and Marsaioli, Anita Jocelyne and Govone, José Silvio and de Franceschi de Angelis, Dejanira and Brienzo, Michel and others (2023) Fungal screening for potential pet depolymerization. Polymers 15(6):1581

Manikandan, Sivasubramanian and Vickram, Sundaram and Sirohi, Ranjna and Subbaiya, Ramasamy and Krishnan, Radhakrishnan Yedhu and Karmegam, Natchimuthu and Sumathijones, C and Rajagopal, Rajinikanth and Chang, Soon Woong and Ravindran, Balasubramani and others (2023) Critical review of biochemical pathways to transformation of waste and biomass into bioenergy. Bioresource technology 372:128679

Marine Debris Archive (2025) marine-debris · github. URL https://github.com/marine-debris, gitHub organization hosting marine debris datasets, code, and resources

Braun Markus and Gruber Christian C and Krassnigg Andreas and Kummer Arkadij and Lutz Stefan and Oberdorfer Gustav and Siirola Elina and Snajdrova Radka (2023) Accelerating biocatalysis discovery with machine learning: A paradigm shift in enzyme engineering, discovery, and design. ACS Catalysis 13(21):14454–14469. https://doi.org/10.1021/acscatal.3c03417

Mellone, Gennaro and De Vita, Ciro Giuseppe and Di Nardo, Emanuel and Coviello, Giuseppe and Di Luccio, Diana and Aucelli, Pietro Patrizio Ciro and Ciaramella, Angelo and Montella, Raffaele (2025) In: , IEEE, pp 526–535

Miller, Tymoteusz and Durlik, Irmina and Kostecka, Ewelina and Kozlovska, Polina and Łobodzińska, Adrianna and Sokołowska, Sylwia and Nowy, Agnieszka (2025) Integrating artificial intelligence agents with the internet of things for enhanced environmental monitoring: applications in water quality and climate data. Electronics 14(4):696

Moorton, Zoe and Kurt, Zeyneb and Woo, Wai Lok (2022) Is the use of deep learning an appropriate means to locate debris in the ocean without harming aquatic wildlife? Marine Pollution Bulletin 181:113853

Moorton, Zoe and Kurt, Zeyneb and Woo, Wai Lok (2024) State of the art applications of deep learning within tracking and detecting marine debris: A survey. arXiv preprint arXiv:240318067

Murphy, Erin L and Bernard, Miranda and Iacona, Gwenllian and Borrelle, Stephanie B and Barnes, Megan and McGivern, Alexis and Emmanuel, Jorge and Gerber, Leah R (2022) A decision framework for estimating the cost of marine plastic pollution interventions. Conservation Biology 36(2):e13827

Nader, Ahmed and Din, Muhayy Ud and Irfan, Mughni and Hussain, Irfan (2024) Object manipulation in marine environments using reinforcement learning. arXiv preprint arXiv:240603223

Nallakaruppan, MK and Gangadevi, E and Shri, M Lawanya and Balusamy, Balamurugan and Bhattacharya, Sweta and Selvarajan, Shitharth (2024) Reliable water quality prediction and parametric analysis using explainable ai models. Scientific Reports 14(1):7520

Ning, Jia and Pang, Shufen and Arifin, Zainal and Zhang, Yining and Epa, UPK and Qu, Miaomiao and Zhao, Jufen and Zhen, Feiyang and Chowdhury, Abhiroop and Guo, Ran and others (2024) The diversity of artificial intelligence applications in marine pollution: A systematic literature review. Journal of Marine Science and Engineering 12(7):1181

Ntana, Fani and Sarazin, Catherine and Figge, Rainer and Mortensen, Uffe (2020) Aspergillus: A powerful protein production platform. Catalysts 10. https://doi.org/10.3390/catal10091064

Oosterhuis, Frans and Papyrakis, Elissaios and Boteler, Benjamin (2014) Economic instruments and marine litter control. Ocean & coastal management 102:47–54

OpenLitterMap (2024) Openlittermap: Open data on plastic pollution. https://openlittermap.com, openLitterMap. Accessed May 9, 2025

Perrin, Elena and Ghini, Veronica and Giovannini, Michele and Di Patti, Francesca and Cardazzo, Barbara and Carraro, Lisa and Fagorzi, Camilla and Turano, Paola and Fani, Renato and Fondi, Marco (2020) Diauxie and co-utilization of carbon sources can coexist during bacterial growth in nutritionally complex environments. Nature communications 11(1):3135

Global Plastics (2022) Global Plastics Outlook — doi.org. https://doi.org/10.1787/de747aef-en, [Accessed 17-09-2024]

Politikos, Dimitris V and Adamopoulou, Argyro and Petasis, George and Galgani, Francois (2023) Using artificial intelligence to support marine macrolitter research: a content analysis and an online database. Ocean & Coastal Management 233:106466

Popescu, Simona Mariana and Mansoor, S and Wani, Owais Ali and Kumar, Shamal Shasang and Sharma, V and Sharma, A and Arya, VM and Kirkham, MB and Hou, D and Bolan, N and others (2024) Artificial intelligence and iot driven technologies for environmental pollution monitoring and management. frontiers in environmental science, 12

Proença, PF and Simões, P (2020) Taco: Trash annotations in context for litter detection. arxiv 2020. arXiv preprint arXiv:200306975

Pedro Proença and Pedro Simões (2024) Trash annotations in context (taco) dataset. https://tacodataset.org, tACO Dataset. Accessed September 21, 2025

Jyotika Purohit (2020) Metagenomic exploration of plastic degrading microbes for biotechnological application. Current Genomics 21(4):253–270. https://doi.org/10.2174/18755488mta2rotau4

Qi, Xinhua and Ma, Yuan and Chang, Hanchen and Li, Bingzhi and Ding, Mingzhu and Yuan, Yingjin (2021) Evaluation of pet degradation using artificial microbial consortia. Frontiers in microbiology 12:778828

Qiu, Jiarong and Chen, Yuxin and Zhang, Liangqing and Wu, Jinzhi and Zeng, Xianhai and Shi, Xinguo and Liu, Lemian and Chen, Jianfeng (2023) A comprehensive review on enzymatic biodegradation of polyethylene terephthalate. Environmental Research p 117427

Qu, Juntian and Xu, Yining and Li, Zhenkun and Yu, Zhenping and Mao, Baijin and Wang, Yunfei and Wang, Ziqiang and Fan, Qigao and Qian, Xiang and Zhang, Min and others (2024) Recent advances on underwater soft robots. Advanced Intelligent Systems 6(2):2300299

Ramos, Edgar and Lopes, Arminda Guerra and Mendonça, Fábio (2024) Application of machine learning in plastic waste detection and classification: A systematic review. Processes 12(8):1632

Râpă, Maria and Cârstea, Elfrida M. and Şăulean, Anca A. and Popa, Cristina L. and Matei, Ecaterina and Predescu, Andra M. and Predescu, Cristian and Donţu, Simona I. and Dincă, Alexandra G. (2024a) An overview of the current trends in marine plastic litter management for a sustainable development. Recycling 9(2):30. https://doi.org/10.3390/recycling9020030, URL https://www.mdpi.com/2313-4321/9/2/30

Râpă, Maria and Cârstea, Elfrida M and Șăulean, Anca A and Popa, Cristina L and Matei, Ecaterina and Predescu, Andra M and Predescu, Cristian and Donțu, Simona I and Dincă, Alexandra G (2024b) An overview of the current trends in marine plastic litter management for a sustainable development. Recycling 9(2):30

Reineke, Walter and Schlömann, Michael (2023) In: . Springer, p 161–290

Richards, Daniel and Worden, David and Song, Xiao Ping and Lavorel, Sandra (2024) Harnessing generative artificial intelligence to support nature-based solutions. People and Nature 6(2):882–893

Sahoo, Subhadeep and Dong, Xiao Han and Liu, Zi Qian and Sahoo, Joydeep (2020) Under water waste cleaning by mobile edge computing and intelligent image processing based robotic fish. arXiv preprint arXiv:200900072 URL https://arxiv.org/abs/2009.00072

Luis F. Salas-Nuńez and Alvaro Barrera-Ocampo and Paola A. Caicedo and Natalie Cortes and Edison H. Osorio and Maria F. Villegas-Torres and Andres F. González

Barrios (2024) Machine learning to predict enzyme–substrate interactions in elucidation of synthesis pathways: A review. Metabolites 14(3):154. https://doi.org/10.3390/metabo14030154

Sales, Julio Cesar Soares and Botelho, Alanna Medeiros and Carvalho, Aparecida Selsiane Sousa and Giudicelli, Luan and de Castro, Aline Machado and Ribeiro, Bernardo Dias and Amaral, Priscilla Filomena Fonseca and Coelho, Maria Alice Zarur (2023) Evaluation of yarrowia lipolytica potential for the biodegradation of poly (ethylene terephthalate)(pet) from mooring lines of oil & gas offshore platforms. Cleaner Chemical Engineering 7:100109

Sannigrahi, Srikanta and Basu, Bidroha and Basu, Arunima Sarkar and Pilla, Francesco (2022) Development of automated marine floating plastic detection system using sentinel-2 imagery and machine learning models. Marine Pollution Bulletin 178:113527

Santos, Murilo R and Dias, Luis C and Cunha, Maria C and Marques, João R (2022) Multicriteria decision analysis addressing marine and terrestrial plastic waste management: A review. Frontiers in Marine Science 8:747712

Sarker, Md Abdul Baset and Imtiaz, Masudul H and Holsen, Thomas M and Baki, Abul BM (2024) Real-time detection of microplastics using an ai camera. Sensors 24(13):4394

Anushka G. Satav and Sunidhi Kubade and Chinmay Amrutkar and Gaurav Arya and Ashish Pawar (2023) A state-of-the-art review on robotics in waste sorting: scope and challenges. International Journal on Interactive Design and Manufacturing (IJIDeM) 17(6):2789–2806. https://doi.org/10.1007/s12008-023-01320-w

Sharifian, Seyedmehdi and Asasian-Kolur, Neda (2022) Polyethylene terephthalate (pet) waste to carbon materials: Theory, methods and applications. Journal of Analytical and Applied Pyrolysis 163:105496

Singh, Amardeep and Jia, Charles and Kirk, Donald (2023) Implementing edge based object detection for microplastic debris. arXiv preprint arXiv:230716289 URL https://arxiv.org/abs/2307.16289

Sinha, Vijaykumar and Patel, Mayank R and Patel, Jigar V (2010) Pet waste management by chemical recycling: a review. Journal of Polymers and the Environment 18(1):8–25

Sivan, Alex (2011) New perspectives in plastic biodegradation. Current opinion in biotechnology 22(3):422–426

Skariyachan, Sinosh and Taskeen, Neha and Kishore, Alice Preethi and Krishna, Bhavya Venkata (2022) Recent advances in plastic degradation–from microbial consortia-based methods to data sciences and computational biology driven approaches. Journal of Hazardous Materials 426:128086

Solis, Wilson Valdez and Parra-Ullauri, Juan Marcelo and Kertesz, Attila (2024) Exploring the synergy of fog computing, blockchain, and federated learning for iot applications: A systematic literature review. IEEE Access

Song, Tao and Pang, Cong and Hou, Boyang and Xu, Guangxu and Xue, Junyu and Sun, Handan and Meng, Fan (2023) A review of artificial intelligence in marine science. Frontiers in Earth Science 11:1090185

Tanasupawat, Somboon and Takehana, Toshihiko and Yoshida, Shosuke and Hiraga, Kazumi and Oda, Kohei (2016) Ideonella sakaiensis sp. nov., isolated from a microbial consortium that degrades poly (ethylene terephthalate). International journal of systematic and evolutionary microbiology 66(8):2813–2818

The Ocean Cleanup (2013) The ocean cleanup. URL https://theoceancleanup.com/

Urso, Mario and Ussia, Martina and Pumera, Martin (2023) Smart micro-and nanorobots for water purification. Nature Reviews Bioengineering 1(4):236–251

Viel, Thomas and Manfra, Loredana and Zupo, Valerio and Libralato, Giovanni and Cocca, Mariacristina and Costantini, Maria (2023) Biodegradation of plastics induced by marine organisms: future perspectives for bioremediation approaches. Polymers 15(12):2673

Walter, Andreas and Sopracolle, Laura and Mutschlechner, Mira and Spruck, Martin and Griesbeck, Christoph (2022) Biodegradation of different pet variants from food containers by ideonella sakaiensis. Archives of Microbiology 204(12):711

Wang, Jian and Wu, Zhengxing and Dong, Huijie and Tan, Min and Yu, Junzhi (2022) Development and control of underwater gliding robots: A review. IEEE/CAA Journal of Automatica Sinica 9(9):1543–1560

Webb, Hayden K and Arnott, Jaimys and Crawford, Russell J and Ivanova, Elena P (2012) Plastic degradation and its environmental implications with special reference to poly (ethylene terephthalate). Polymers 5(1):1–18

Wen, Shuixiu and Zheng, Wen and Bornscheuer, Uwe T and Wu, Shuke (2025) Generative artificial intelligence for enzyme design: Recent advances in models and applications. Current Opinion in Green and Sustainable Chemistry 52:101010

Willis, Kathryn A and Serra-Gonçalves, Catarina and Richardson, Kelsey and Schuyler, Qamar A and Pedersen, Halfdan and Anderson, Kelli and Stark, Jonathan S and Vince, Joanna and Hardesty, Britta D and Wilcox, Chris and others (2022) Cleaner seas: reducing marine pollution. Reviews in Fish Biology and Fisheries 32(1):145–160

Xie, Wen Jun and Warshel, Arieh (2023) Harnessing generative ai to decode enzyme catalysis and evolution for enhanced engineering. National Science Review 10(12):nwad331

Yan, Zheng-Fei and Xu, Ke-Wei and Wu, Jing (2023) Synergism between multi-pseudomonas and cutinase for biodegradation of crude oil-based derivatives. Current Microbiology 80(1):30

Yang, Zhenze and Ye, Weike and Lei, Xiangyun and Schweigert, Daniel and Kwon, Ha-Kyung and Khajeh, Arash (2024) De novo design of polymer electrolytes using gpt-based and diffusion-based generative models. npj Computational Materials 10(1):296

Yip, Aaron and McArthur, Owen D and Ho, Kalista C and Aucoin, Marc G and Ingalls, Brian P (2024) Degradation of polyethylene terephthalate (pet) plastics by wastewater bacteria engineered via conjugation. Microbial Biotechnology 17(9):e70015

Yoshida, Shosuke and Hiraga, Kazumi and Takehana, Toshihiko and Taniguchi, Ikuo and Yamaji, Hironao and Maeda, Yasuhito and Toyohara, Kiyotsuna and Miyamoto, Kenji and Kimura, Yoshiharu and Oda, Kohei (2016) A bacterium that degrades and assimilates poly (ethylene terephthalate). Science 351(6278):1196–1199

Youssef, SM and Soliman, M and Saleh, MA and Mousa, MA and Elsamanty, M and Radwan, AG (2022) Underwater soft robotics: A review of bioinspiration in design, actuation, modeling, and control. micromachines 2022, 13, 110

Zhang, Wenbo and Zhao, Yuchen and Li, Fangjing and Zhu, Hongbo (2023a) A hierarchical federated learning algorithm based on time aggregation in edge computing environment. Applied Sciences 13(9):5821

Zhang, Y. and Smith, J. and Lee, A. (2023b) Enhancing marine debris identification with convolutional neural networks. Journal of Emerging Investigators 6(1):150–160. URL https://emerginginvestigators.org/articles/23-150

Zhao, Sufang and Liu, Renju and Wang, Juan and Lv, Shiwei and Zhang, Benjuan and Dong, Chunming and Shao, Zongze (2023) Biodegradation of polyethylene terephthalate (pet) by diverse marine bacteria in deep-sea sediments. Environmental Microbiology 25(12):2719–2731

Zheng, Ying and Yanful, Ernest K and Bassi, Amarjeet S (2005) A review of plastic waste biodegradation. Critical reviews in biotechnology 25(4):243–250

Zheng, Ziqiang and Zhang, Jipeng and Vu, Tuan-Anh and Diao, Shizhe and Tim, Yue Him Wong and Yeung, Sai-Kit (2023) Marinegpt: Unlocking secrets of ocean to the public. arXiv preprint arXiv:231013596

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- Declaration of generative AI and AI-assisted technologies in the manuscript preparation process: During the preparation of this work, the authors used ChatGPT of OpenAI and Gemini of Google for language refinement and paraphrasing. After using the aforementioned tools/services, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.
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