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To what extent solid waste could be managed through intelligent approaches?

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Waste management has been considered an antecedent of delivering environmental sustainability. However, the present conventional waste management approaches have several difficulties in addressing the significance of effectively managing solid waste to avoid health and environmental problems. Therefore, the present research aims to identify intelligent approaches to tackle the issue of managing solid waste. The present study conducts a systematic literature review through bibliometric and content analysis of 226 relevant articles using the Scopus database. The findings from the descriptive bibliometric analysis highlight the year-by-year publication trend, significant publication sources, affiliation statistics of various institutions, and an analysis of the corresponding author's nation. Furthermore, the content analysis offers three clusters based on artificial intelligence, machine learning techniques, and the Internet of Things. Also, based on the findings, the article provides a research framework to offer a thorough understanding of the use of different intelligent approaches in managing solid waste. This present research offers a thorough understanding of the impact of different intelligent approaches in managing solid waste. Also, the given research framework summarises and highlights how intelligent approaches are managing solid waste and what will be the possible outcome in doing so.

Keywords: artificial intelligence/intelligent approaches/machine learning/solid waste management/UN SDG 13: Climate action

1. Introduction

The population is growing, and industrialisation is accelerating, which caused a notable enhancement in solid waste generation. Manufacturing procedures, as well as the handling and discarding of goods in commercial, industrial, building, and household contexts, may be the source of this waste. Solid waste is a broad category that includes litter, debris, discarded products, and rubbish. Solid waste is frequently produced in various forms, including metal, glass, plastic, and organic materials. On a global scale, annual solid waste output typically ranges from 7 to 9 billion tonnes, with municipal solid waste (MSW) accounting for about 2 billion tonnes in 2016 (Chen *et al*., 2020). The latest study indicates that worldwide production of MSW is predicted to increase, reaching 2.59 billion tonnes by 2030 and may be 3.40 billion tonnes by 2050 (Kaza *et al*. 2018).

Research has indicated that a lack of proper planning and ineffective operational practices significantly contribute to poor waste management. Recently, significant endeavours have been aimed at transforming the waste management sector into a more sustainable and profitable industry by utilising advanced technologies and intelligent systems.

Improper management of MSW disposal can lead to polluted surroundings, contribute to the development of toxic waste and environmental contamination, and promote the spread of diseases through rodents and insects (Alotaibi and Nassif, 2024: Kurniawan *et al.*, 2021). For developing effective waste management, accurate predictions of MSW are essential. Forecasting MSW accurately is essential for building successful waste management systems (Anjum *et al.*, 2022) and optimising the usage of existing infrastructure (Ceylan, 2020). In the conventional approach, the anticipation of MSW generation has been facilitated through a range of forecasting tools, including descriptive statistical analysis, regression analysis, time series analysis, and material flow analysis (Ayeleru *et al.*, 2021; El Jaouhari *et al.* 2025). Despite their efficiency, all these approaches have benefits and drawbacks. Instead of relying on a single strategy, it is more logical to measure the performance of different methods to find the best one. Due to the availability of more data and technology, predictive models have gained more popularity recently in intelligent approach applications. On the other hand, energy recovery, composting, and recycling contribute positively to the reduction of MSW. In recent years, resource recovery from waste has attracted much attention. Solid waste management (SWM) is the collection, treatment, and disposal of solid waste products, as well as the location of landfills (Hai *et al.*, 2022; Yaman *et al.*, 2020). Good SWM practices need to be strictly enforced because of the different hazards associated with solid waste including toxicity, flammability, infectivity, and radioactivity (Sudha *et al.*, 2016). There are many hazards in such waste generation; hence, appropriate management of the generated MSW itself is required to protect and preserve the environment. SWM will help remove negative effects on public health and the ecosystem, but also the protection of natural resources. Accurate prediction of MSW is an important step for the development of an effective waste management strategy. However, lately, several studies have proven the implementation of artificial intelligence (AI) and machine learning (ML) approaches into other scenarios in waste management has been successful. These models have been used to predict the generation of MSW, collection process, sorting process, and landfill sites (Ayeleru *et al.*, 2021; Chu *et al.*, 2018).

While sustainable waste management practices are being constantly practised, recycling rates remain poor under traditional SWM systems. This increases pressure on landfills, worsening environmental and health challenges (Global Waste Index, 2022). Landfills not only contribute to pollution but also are created at the cost of natural habitats, leading to wildlife displacement. In the United States alone, more than 3000 active landfills have consumed approximately 1.8 million acres of habitat, highlighting the pressing need for more sustainable waste management solutions due to new technologies that are helping with this challenge (University of Colorado Boulder, 2021). AI-based automated sorting systems have brought about a revolutionary change in waste management. Robotics and ML are enabling these systems to sort waste more effectively. The AI algorithms are trained to recognise the various categories of waste generated by different households and businesses. More importantly, EverestLabs created a dataset of over 5 billion recyclable items to train their algorithms in three dimensions looking through the profiles. These systems remain conscious of how waste compositions change over time and continue to recalibrate themselves. One such robotics platform that sorts waste very precisely and efficiently in the recycling chain is RecycleOS (www.everestlabs.ai/recycleos). Recently, due to the increased availability of data and advances in technology, the use of various AI techniques has been more prevalent in predictive models. These techniques, however, are designed as a replication of human thought when tasked with solving complex engineering problems that have multiple inter-linking variables. ML regression techniques automatically learn from training data and predict forthcoming outcomes using novel input data samples (Ayeleru *et al.*, 2021; Liang *et al.*, 2021). Lately, the application of AI and ML models has seen considerable increase such as Support Vector Machines (SVM), Gaussian Processes Regression, Random Forest (RF), Neural Networks (NN), Multivariate Adaptive Regression Splines (MARS), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Linear Regression analysis (LR), Multi-Layer Perceptron (MLP), K-Nearest Neighbours (K-NN), Convolutional Neural Network (CNN), Decision Tree (DT), Deep-Learning (DL), and Artificial Neural Networks (ANN) (Altikat *et al.*, 2022; Anjum *et al.*, 2022; Ghanbari *et al.*, 2021; Ihsanullah *et al.*, 2022). This recent growing interest in these models can be found in their spectacular versatility and proven power to make good predictions. The conventional manual waste-collection process adversely affects the efficacy of waste management. This causes negative outcomes of overfilled garbage bins: the transmission of diseases, the emission of toxic gases, and the risk of fire that is indeed harmful to both the environment and humans (Magazzino *et al.* 2020; Munir *et al.*, 2023). The Internet of Things (IoT) offers a remedy to this problem through the implementation of radio-frequency identification (RFID), sensor-integrated waste containers, and GPS-integrated routing processes (Medvedev *et al.*, 2015). These devices with sensors help to determine the location of waste, thus enabling the timely removal of filled bins. The research in the waste management sector focuses on either individual approaches or the integration of multiple intelligent environmental and waste management techniques, such as AI, ML, and IoT. Table 1 summarises the review articles related to the application of digital technologies including AI and ML in the field of MSW management, which also highlights how the present study differs from prior efforts. As per the author's knowledge, intelligence-based management for MSW research is limited, and no one has comprehensively reviewed intelligent approaches for MSW; this study covers this gap by formulating two research questions as follows:

RQ1: What specific roles do intelligent approaches, such as AI, ML, and the IoT, play in improving the efficiency and effectiveness of MSW management systems?

RQ2: In what ways do these intelligent approaches contribute to optimising waste collection, segregation, recycling, and disposal processes within MSW management?

The present research addresses the research questions mentioned above by conducting a systematic literature review (SLR), which mainly focuses on recent advances in managing MSW using intelligent approaches. Earlier review articles addressed the challenges of MSW and proposed several solutions. However, no review article has conducted a comprehensive study of MSW using both bibliometric and content analysis. In our article, we performed a bibliometric analysis combined with content analysis. We conducted the SLR using bibliometric and content analysis of 226

Table 1. Synopsis of digital techniques applied to MSW studies

Digital technology used	No. of articles	Time range	Focus of study	Outcomes	References
ANN, SVM, DT, GA	32	2013–Nov 2023	A systematic review of MSW management using ANN for low-carbon transition.	This study focused on the use of the ANN model in MSW for the prediction of trends related to greenhouse gas emissions.	Hoy *et al*. (2024)
GA, ANN, SVM, KNN, MLR	N/A	N/A	This study focused on to use of AI and various optimisation techniques for MSW generation, collection, treatment, and disposal.	This research also explores how advanced ML techniques can be used to forecast waste and select sites for disposal.	Sree and Kanmani S (2024)
SVM, DT, GA, RF, MLP, ANN, CNN, RNN, KNN, DNN,	N/A	N/A	Recent AI applications for solid waste management literature review.	AI techniques are trending in nature to MSW management for generation, separation, and disposal.	Ihsanullah *et al*. (2022)
ANN, DT, SVM, GA	98	2005–2021	The purpose of this study is to conduct a comprehensive analysis of the applications of artificial intelligence for municipal solid waste in Australia.	AI-based models prove more effective than traditional methods in predicting waste generation and recycling, highlighting the need for upgraded recovery infrastructure.	Andeobu *et al*. (2022)
SVM, RF, ANN, MARS, ANFIS, LR, K-NN, CNN, DT, IoT, hybrid techniques	226	2013–Dec 2024	Where the above-mentioned studies emphasise applications and challenges of AI and ML in waste management, this study provides a thorough and strategic framework for the comprehensive adoption of AI, ML, and IoT in MSW, closing the gaps in academia and industry for sustainable development in the waste management sector.	Municipal solid waste management using digital technology such as AI, ML, and IoT improved efficiency in solid waste forecasting, monitoring, and planning. Our study provides an in-depth assessment and a strategic framework for the implementation of AI, ML, and IoT in MSW management.	Current study

Source(s): created by authors

articles selected from the Scopus database. The bibliometric and content analyses worked together and allowed us to identify MSW areas (generation, disposal, segregation, forecasting, and gathering) through intelligent approaches. After content analysis, a research framework is proposed to offer a thorough understanding of the past research relevant to the impact of intelligent approaches in managing MSW.

Section 2 covers the methodology part, while Section 3 covers bibliometric analysis. Section 4 presents content analysis, while Section 5 explores the discussion of the articles. Section 6 shows the implications of the research, and Section 7 provides the conclusion along with the limitations of the study and future research directions.

2. Methodology

The present research offers SLR, where SLR is an organised strategy that builds knowledge about a particular area of study using data from various sources. SLR is based on a rigid set of guidelines. Therefore, the procedure is transparent, scientific, and repeatable. SLRs that use rigorous selection processes, investigation, and reporting procedures combine existing information from numerous sources to produce new knowledge (Samadhiya *et al.*, 2023a).

2.1 Database for literature review

The articles were extracted from the Scopus database. The Scopus database was selected because it has a large body of literature, can be easily accessed by academic institutions, and has been used for SLR in related research fields (Tennakoon *et al.*, 2023). Scopus offers numerous articles and papers from reputable publications in technology, management, health, and the social sciences, making it one of the most prominent abstract and reference databases (Sharma *et al.*, 2021). International collaboration analysis can be performed either by counting same-country or different-country articles based on the Scopus database. This means that each article can be published in one country (e.g. Sweden) or multiple countries (e.g. France, Spain, Italy, and Australia) classes as single-country publication (SCP) or multiple-countries publication (MCP), respectively. SCP and MCP are also examples of this intra-country collaboration and international collaboration.

2.2 Screening of article

Two main search strings are selected with several keywords for screening the Scopus database. The specified keywords are connected in these search strings with Boolean connectors like 'OR' and 'AND' to provide a deeper examination relevant to the research field. For this study, we used the logical operator 'OR' to connect the identified keywords and the 'AND' operator to combine the phrases' keywords. Using the Boolean operators 'OR' and 'AND', the following search string was created: ('waste man' OR 'sustain' OR 'trash man' OR 'Waste adm' OR 'recycle' OR 'sustainable waste' OR 'municipal solid' OR 'municipal waste') AND ('artificial intelligence' OR 'machine learning' OR 'big data' OR 'intelligent system' OR 'intelligent approach').

2.2.1 Inclusion and exclusion criteria

We have set up inclusion and exclusion criteria to make sure we use research findings that match our requirements. 'The Title-Abstract-Keywords' fields of the databases provided a total of 2519 documents through a search. We have selected the last decades because the articles that were published before this decade were not significantly relevant to the context of the present article. Therefore, this search article focused on peer-reviewed papers published between 2013 and 2024 (December) and this yielded 2263 documents. Next, searches conducted on the Scopus databases were restricted to journal articles available in English. We excluded review articles to eliminate the possibility of bias from prior literature reviews (Wijewickrama *et al.*, 2021). A total of 1154 articles were obtained from these searches and then sorted for further refinement. Next, the criteria for excluding content in the current study involve book chapters, editorials, letters, notes, and surveys. This yielded 1118 documents. Furthermore, the open-access journals were excluded, resulting in a remaining count of 545 papers. Figure 1 depicts the refining procedure used in this investigation.

2.3 Selection of related studies

In the initial screening, 545 articles were extracted after inclusion–exclusion criteria, and their titles and abstracts were checked for suitability for the research domain. If the article title and abstract do not provide proper information, their introduction and conclusion are reviewed to assess their relevance to the study. Consequently, 319 papers unrelated to our research question were removed, resulting in a final selection of 226 papers. After that, we conducted bibliometric analyses on these selected 226 papers chosen for review. Using an information extraction approach, the features of all of our studies were presented, including the annual production of journal papers, most globally cited documents, most relevant affiliation, most relevant source, and the country of corresponding authors.

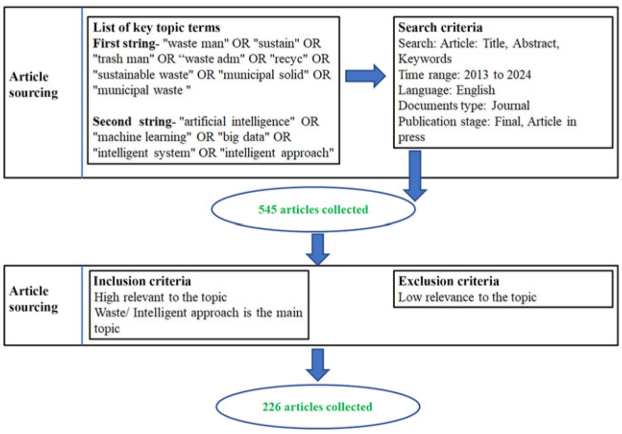

Figure 1. Selection process of articles (source:(s): created by authors)

3. Bibliometric analysis

Bibliometric analysis is a collection of analytical tools and methodologies to identify outstanding authors, seminal work, and distinct research trends (Donthu *et al.*, 2021). Many literature reviews in the social sciences and management have employed bibliometric analysis in recent years. Samadhiya *et al.* (2023b) used an R-tool for bibliometric research on blockchain technology in reverse logistics. Tsai *et al*. (2020) used VOSviewer software in their literature review on MSW management in a circular economy. The main information from collected articles used for the literature review is shown in Table 2. Table 2 summarises 226 publications found in the Scopus database from 2013 to 2024 (December). The annual growth rate percentage of the articles was 28.48. From the collected articles, a total of 909 authors have contributed; out of these, six papers have a single author. The average number of co-authors per document is 4.86. Table 2 also shows author collaboration, citations per document, and author keywords.

3.1 Trend of publications

The variation of MSW through intelligent approaches articles by publication year from 2013 to 2024 is shown in Figure 2. In the early stages, there is little to no interest among researchers and practitioners in integrating intelligent approaches into waste management. Figure 2 displays that only a few articles were published between 2013 and 2017. However, from 2018 to 2024, there was an increase in this area, indicating a growing use of intelligent approaches for managing waste. The number of publications increased by 86% between 2018 and 2019. From 2019 to 2020,

Table 2. Main information about the collected article

Description	Results
Dataset primary information	—
Timespan	2013–2024
Documents	226
Annual growth rate: %	28.48
Document average age	3.17
Average citations per doc	17.75
References	11510
Authors	—
Authors	909
Authors of single-authored docs	6
Authors collaboration	—
Single-authored docs	6
Co-authors per doc	4.86
International co-authorships: %	33.63

Source(s): created by authors

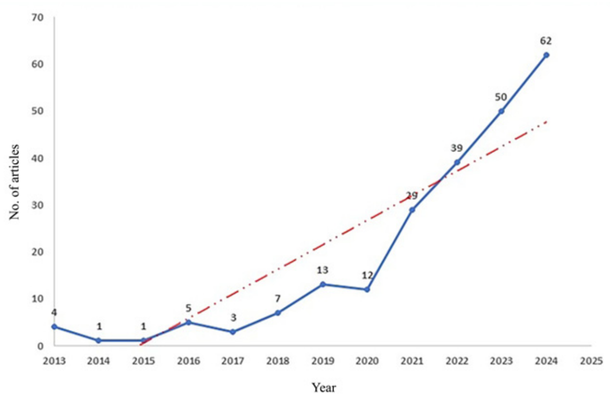

Figure 2. Year-wise trend of publications (source:(s): created by authors)

there was not much of a change, but from 2020 to 2021 again, a publication growth of 141% was observed. The trend of publications was seen in 2021–2022, 2022–2023, and 2023–2024, with increments of 34%, 28%, and 24%, respectively, over these periods.

3.2 Publishing source and keywords used

The quantity of articles published in various journals from 2013 to 2024 is displayed in Table 3. The top journals that publish the most articles overall include '*Waste Management*' (27), '*Journal of Cleaner Production*' (19), '*Journal of Environmental Management*' (9), '*Science of the Total Environment*' (9), '*Waste Management and Research*' (9), and '*Resources, Conservation and Recycling*' (8). In addition to this, the journal '*Chemosphere*', '*Energy*', '*Environmental Science and Pollution Research*', '*Environmental Science and Technology*', and '*Journal of Hazardous Materials*' have published five papers.

Figure 3 shows the treemap of the keywords obtained with Bibliometrix R-tool. The treemap shows that the most frequently used words in this literature are MSW, waste management, ML, solid waste, article, china, waste disposal, AI, and recycling.

Table 3. Journal-wise statistics of articles published in waste management achieved by way of intelligent approaches

Sources	Articles
Waste Management	27
Journal of Cleaner Production	19
Journal of Environmental Management	9
Science of the Total Environment	9
Waste Management and Research	9
Resources, Conservation and Recycling	8
Chemosphere	5
Energy	5
Environmental Science and Pollution Research	5
Journal of Hazardous Materials	5
Others	125

Source(s): created by authors

3.3 Affiliation statistics

The top ten papers on waste management using intelligent approaches are shown in Table 4. Academic institutions from China, Iran, and Canada have made remarkable contributions to published papers on waste material management through intelligent approaches. Tongji University has published the most research papers, with a total count of 31. Following Tongji University, Tsinghua University has published 29 articles, while the Hong Kong Polytechnic University and Tianjin University participated in the publication of 24 and 20 papers, respectively. Table 4 clearly shows that Chinese institutions have published the maximum number of articles utilising intelligent approaches for waste materials.

3.4 Authors' production over time

Figure 4 shows the timeline of publications by several authors on intelligent approaches for SWM. The size of the circle shows how many publications there are, and the darkness of the circle shows how many citations were made in a given year (TC/Y). Figure 4 shows that Abbasi, affiliated with Griffith University in Australia, was the most productive, with five publications. His research mainly focused on combining AI and ML approaches for forecasting MSW generation. Figure 4 also shows that Abbasi has published articles for a longer time frame (2013–2021) than the other authors. Zhao from Tongji University in Shanghai, China, works based on MSW production and diversion factors, utilising DL methods, and they also used a CNN to estimate MSW. Zhu, from Sun Yat-Sen University in China, contributed four articles to our findings. The frequency of articles of some authors who have published papers between 2021–2022 and 2022–2024 is higher than in previous years.

3.5 Analysis of the corresponding author's country

Based on the articles selected, waste management attained by way of intelligence methods has a broad publishing coverage in the world. Figure 5 shows the distribution of research papers per country. Among the 226 selected pieces of papers, China (63 papers) is the most active contributor. Also, India, Iran, and the USA are the top contributing countries in waste management studies using intelligent approaches. India, Iran, and the USA published 34, 14, and 9 articles, respectively. We also found that three papers from Bahrain are MCP, while three papers from Japan are SCP.

4. Content analysis

While reviewing 226 selected articles on intelligent approaches to MSW management, our research found that the literature primarily focuses on the use of AI, ML, and the IoT. The remaining articles were also situated within the broader category of AI, ML,

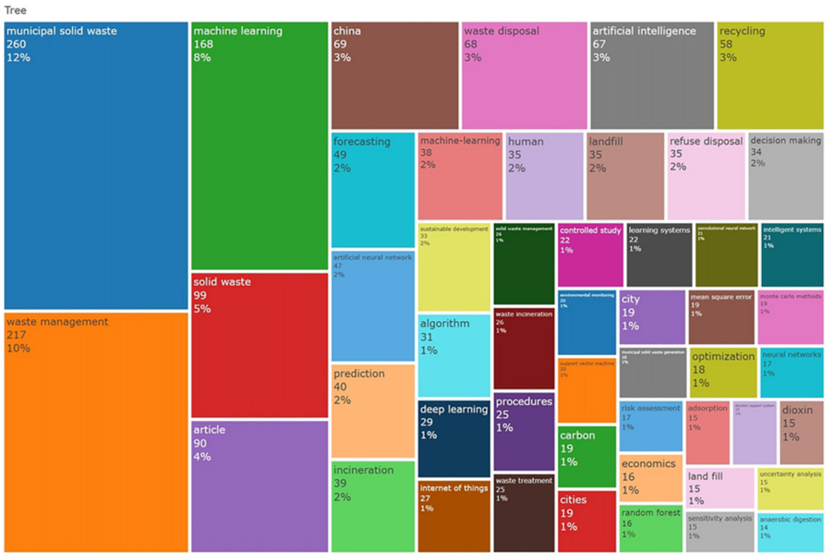

Figure 3. The keyword treemap includes all finished articles (source:(s): created by authors)

Table 4. Institute-wise articles published in waste management through intelligence approaches

Affiliation	Country	Articles
Tongji University	China	31
Tsinghua University	China	29
The Hong Kong Polytechnic University	China	24
Tianjin University	China	20
Tianjin University of Commerce	China	19
Shanghai Jiao Tong University	China	18
School of Environment	China	16
Zhejiang University	China	14
Islamic Azad University	Iran	10
University of Regina	Canada	10

Source(s): created by authors

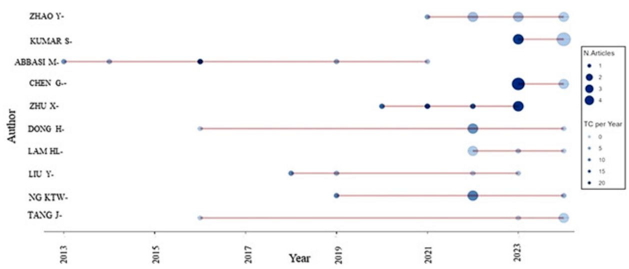

Figure 4. Authors' publications over time in SWM through intelligent approaches (source:(s): created by authors)

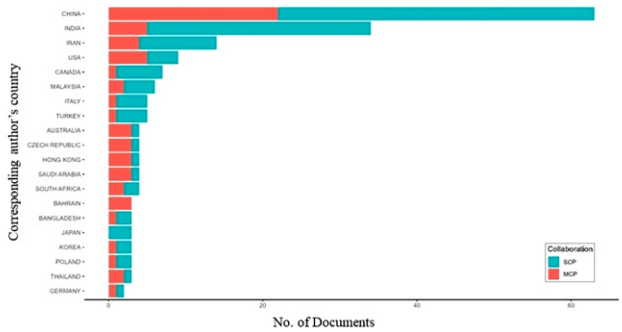

Figure 5. Most relevant countries by corresponding author (source:(s): created by authors)

and IoT, which prompted the creation of a cluster dedicated to AI, ML, and IoT. Therefore, based on the number of articles in each cluster, three major clusters are created using intelligent waste management techniques. The major clusters are managing waste through AI-based waste management, ML techniques, and IoT-based intelligent approaches used for waste management. Cluster 1 is comprised of 61 articles, Cluster 2 contains the largest number of 94 articles, and Cluster 3 contains 71 articles.

4.1 Cluster 1: AI-based waste management

AI is a primary intelligent approach to managing waste in this cluster. The application of AI-based approaches in SWM has been recorded by several studies, which have found that these methods may be applied to predict and enhance procedures, such as MSW production, detection, collection, and classification (El Jaouhari *et al.*, 2025; Liang *et al.*, 2021). AI can change the way we deal with waste in the future. Researchers utilise AI-based methods to improve and predict the efficiency of SWM systems. Hai *et al.* (2022) investigated a single ML algorithm based on evolutionary AI. To lessen the negative effects that CO_2 emissions have on the environment, they suggest a genetic algorithm that is based on AI. The MSW is processed in the waste treatment plant in preparation for the digester. The combined energy system uses the digester's produced biogas as fuel. Their system is modelled with technical and economic aspects in mind, and the impact of key design elements is anticipated. The finding shows that the AI-based system reduced greenhouse gas (GHG) emissions more successfully than the standard approach. Pitakaso *et al.* (2024) combined AI technologies to categorise medical-related municipal waste. They proposed a new model that used deep learning algorithms and CNNs and it was found that this model enhanced municipal waste segregation accuracy from 2.02% to 8.80%. The performance of their new model is more than the conventional models such as BiLSTM and CNN-GLSTM. Ghanbari *et al.* (2023) explored utilising a model that uses AI techniques and ensemble empirical mode decomposition models to enhance the accuracy of monthly predictions for MSW generation. The projected model's performance was subsequently estimated by comparing it to other established single models. Based on the uncertainty analysis results, the predictive models worked better than the input factors in SWM prediction.

4.2 Cluster 2: Managing waste through machine learning techniques

During the content analysis, we have identified the second cluster as managing waste through ML techniques. We have looked at the articles in the direction of MSW with the help of implementing ML techniques; in doing so, we identified 94 articles under this cluster. This cluster revolves around managing waste through ML techniques such as ANN, RF, SVM, DT, ANFIS, and KNN algorithms. Abbasi and El Hanandeh (2016) aim to create a model that can accurately predict monthly MSW generation. This will help waste-related organisations build and run better MSW management systems. They employed four intelligent approaches: SVM, ANFIS, ANN, and KNN. The outcomes show that models have high prediction accuracy and could be effectively applied to MSW forecasting models. ML algorithms can accurately forecast MSW production by training with waste generation time series. Their study shows that all the models for waste forecasting are accurate and reliable, but the ANFIS model suggests that it is more accurate than other models. Kannangara *et al.* (2018) built models for estimating the production of MSW in Canada. The major goal of the research was to create models for accurately estimating the production of MSW. The models were developed using two ML algorithms: decision trees and neural networks. Demesouka *et al.* (2013) estimated the feasibility of prospective MSW landfill locations in north-eastern Greece. They accomplished this by combining Geographic Information Systems, Analytic Hierarchy Process, and compromise-programming techniques. Kumar *et al.* (2018) investigated the relationship between the potential for the production of plastic waste among various socio-economic categories. The research demonstrates that the maximum rates of polyethylene terephthalate and high-density polyethylene plastic generation were observed in households across all socio-economic groups. They created and evaluated three non-linear ML algorithms, namely ANN, SVM, and RF, to forecast the rate at which plastic waste is produced. Abu-Qdais *et al.* (2024) used the ML models and noticed that a combination of models showed more accuracy as compared with individual models. In their work, they used six classes of solid wastes (paper, cardboard, glass, alloys, plastics, and mixed waste) and found that the trash-net data accuracy is 96.06% and local garbage accuracy is 94.40%. Magazzino *et al.* (2020) did a study to explore the relationship between MSW production and GHG emissions. They used time series methods and an ML technique in their study. Their research showed that the generation of urban waste is a major contributor to GHG emissions in the waste segment, while proper handling of waste plays a key role in reducing GHG emissions. Singh *et al.* (2024) used ML techniques to forecast and optimise biogas generation yield from organic fractions of MSW. The data set was taken as fresh, 3-month-old, 4-month-old, and 3- and 5-year-old MSW. The models used in their study are ANN, LR, RF, SVM, and XGBoost. The outcomes show that the XGBoost and RF models had high R^2 values (0.88 and 0.68) and low root mean square error (305 and 496) values, which indicate higher accuracy prediction of MSW generation. Furthermore, the LR model had moderate results and ANN models showed less accuracy among them.

4.3 Cluster 3: IoT-based intelligent approach

After the Internet, the IoT is viewed as a technology and economic wave in the worldwide information economy. Traditional methods of waste management have become ineffective and outdated. It is challenging to monitor waste generation, collection, and disposal (Wang *et al.*, 2021). Identifying and removing trace bins is made simple using intelligent approaches, and they can be emptied before they get too full. It is also possible to forecast how much garbage will be generated with the help of a smart bin through intelligent approaches. For instance, Wang *et al.* (2021) created an innovative municipal waste classification concept using a cloud computing method to achieve high waste classification accuracy. To reach a high level of precision, the smart bins are outfitted with a collection of gas sensors and ultrasonic wave sensors for real-time monitoring of abnormally released gases. Before garbage collection, the garbage is divided into nine categories to make the disposal process easier and their study showed that vehicle routing and collection plans are critical components of an efficient waste management system. Xue *et al.* (2019) suggested a novel collecting methodology to keep up with information and communication technologies (ICTs) in SWM. Several rising corporations are involved in the intelligent recyclable collection, in which human–human and human–machine connections are critical components. The intelligent collection concept proposes using ICTs and the IoT to facilitate waste collection or recyclables. This collecting approach provides benefits regarding organisation, logistics, and data collection. Ramson *et al.* (2022) created a self-powered, IoT-enabled trace bin with an effective control mechanism for measuring the filling levels of waste bins. The module used a microcontroller and had ultrasonic sensors. The ultrasonic sensor (MB1010 LV-Maxsonar-EZ1) determines the unfilled level of containers. The wireless connectivity in the developed system is achieved through long-range (LoRa) technology, and the battery benefits from an extended lifespan due to its solar charging panel. Idwan *et al.* (2020) created an IoT-powered SWM system that used GA to discover the optimum path for the waste truck fleet. Their study's primary objectives were reducing road traffic and removing solid waste quickly. They created an algorithmic technique that allowed dumpsters to connect wirelessly to the municipal authority server, providing updates on waste levels. Alqahtani *et al.* (2020) proposed employing the NN-based cuckoo search algorithm for smart waste bin monitoring. They employed IoT devices to keep track of people's actions and analyse waste characteristics. Henaien *et al.* (2024) developed an advanced IoT smart system for stakeholders concerning waste management systems. They have used GPS sensors, LED indicators, and ultrasonic sensors in garbage bins along with LoRa in their study to monitor solid waste status. They employed vehicle routing problems and applied ML algorithms for route optimisation. This technology ensures that smart bins are monitored in real time. When the garbage bin fills a particular range, the sensors send signals to the waste collection system for timely waste collection along with suggestions of the optimum route, which minimises the chances of overfilled bins and reduces the transportation cost by eliminating unnecessary movement of vehicles.

5. Discussion and implications

Due to increased urbanisation and population growth, waste management has become a critical issue in the modern world (Chen *et al.*, 2020). Intelligent technologies are to be integrated into waste management systems to completely revolutionise waste management procedures (Anjum *et al.*, 2022; Ayeleru *et al.*, 2021). For instance, the use of intelligent techniques such as AI and ML methods to assist waste classification has become a significant part of waste management and also for environmental sustainability processes. This paper's main objective is to show how to manage municipal waste management through intelligent approaches.

AI, ML, and IoT are taken as intelligent approaches, and multiple algorithms used for managing the waste are taken as assisted approaches, as shown in Figure 6. These assisted approaches are intelligent approaches to managing waste. For effective implementation of these intelligent approaches, many algorithms are used, such as GA (Król *et al.*, 2016), Clustering Algorithms (Adeleke *et al.*, 2023), ANN (Ayeleru *et al.*, 2021), ANFIS (Abbasi and El Hanandeh, 2016), and gradient descent (Coskuner *et al.*, 2020). Various outcomes are found using these types of approaches in waste management. Solano Meza *et al.* (2019) employed three AI-based models to determine how much waste would be made in Bogota, Colombia. Their analysis of this forecast considered factors such as the city's collection zone distribution, socio-economic stratification, population, and quantity of waste produced during various months. The modelling outcomes show SVM is the best model. Ghanbari *et al.* (2021) estimated MSW generation in Tehran, Iran, based on socio-economic factors. They employed Pearson's correlation analysis to identify and select the most relevant variables: income, population, GDP, and time of year. This study used the MARS model and the optimised

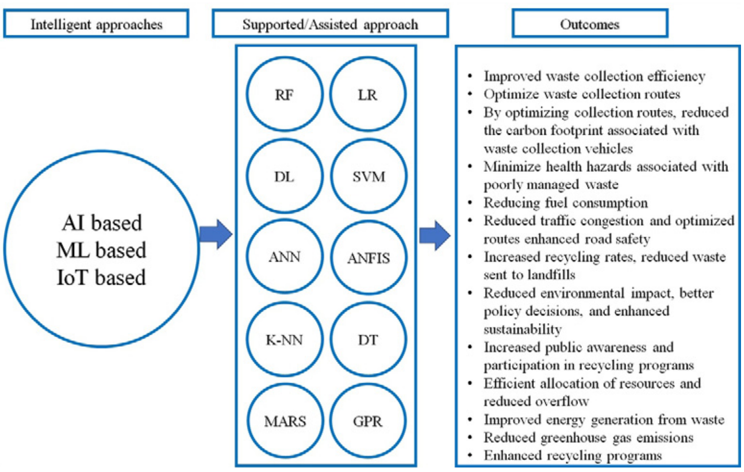

Figure 6. Framework for the use of intelligence approaches in SWM (source:(s): created by authors)

crow search algorithm (CSA) to increase accuracy. Compared with the results of stand-alone and hybrid optimised models, the MARS-CSA model best forecasts solid waste generation data.

For recycling and management to be done effectively and efficiently, MSW must be collected and separated. Human labour is required to manually sort waste, which results in numerous serious illnesses. Aishwarya *et al.* (2021) introduce an image-processing application that uses ML to sense objects. Their work aims to detect non-biodegradable objects such as plastic, metal, and glass in the bin. For training the model, 450–500 images are considered. The result shows that a maximum accuracy of 75% is obtained for detecting metal objects. Waste classification through intelligent approaches is critical to waste management and environmental sustainability efforts. Sudha *et al.* (2016) used AI's deep learning techniques to distinguish between biodegradable and non-biodegradable goods. Their research concentrated on identifying and classifying waste disposed of in garbage. They found that implementing automated systems improved garbage sorting and classification efficiency compared with manual approaches. In another study, Chu *et al.* (2018) utilised a multilayer hybrid deep-learning system (MHS) that can automatically categorise waste left by people in urban public areas. They recorded waste photos using a high-resolution camera and utilised sensors to find relevant features. The MHS employs a CNN-driven algorithm for extracting photo characteristics and utilises an MLP method to integrate these characteristics with other data. Vrancken *et al.* (2019) use of Deep Convolutional Neural Networks demonstrated encouraging results in distinguishing between different types of paper and cardboard. These approaches have the potential to improve waste classification procedures. Their model exhibited an average accuracy ranging from 61.9% to 77.5%.

Bin-level detection models attempt to predict the levels of content in waste bins. Typically, the real-time data are collected from the level sensors or smart waste bins using installed cameras (Abdallah *et al.*, 2019). The underlying processes of IoT applications in a smart city intelligent waste management system have been explored. Data were collected using RFID, GPS, and other sensors. These devices included information about use, disposal, and waste type. This information was effectively used by the control centre to initiate the necessary actions in due course. This continuous cycle contributed to the cleanliness of the urban context. Hannan *et al.* (2016) discovered that the KNN classifier outperformed the MLP in classifying bin levels, achieving 95% and 97% accuracy rates, respectively. In their investigation, a total of 120 L bins were utilised. Ramson *et al.* (2021) showed a self-powered IoT system to monitor waste bins' unfilled capacity. In their study, the terminal sensor nodes in the IoT system, referred to as bin level monitoring units (BLMUs), are strategically placed within each trash bin requiring unfilled level monitoring. These BLMUs measure the bins' unfilled level and transmit the data to a wireless access point unit (WAPU). Multiple BLMUs send their unfilled level information to a single WAPU, which uploads the aggregated data to the main server for analysis. Gutierrez *et al.* (2015) used an IoT equipped with sensors that can read, gather, and send garbage capacity data over the Internet; they demonstrate a waste-collecting solution based on giving trashcans intelligence. Waste collection techniques can be managed dynamically and effectively using these data when it is processed using graph theory optimisation algorithms in a spatiotemporal environment. The results show that waste collection strategies based on real-time trashcan filling status improve waste collection efficiency by ensuring that trashcans are collected on the same day when they get full.

5.1 Implications

This study offers practitioners or management professionals insight into how intelligent approaches can help them attain SWM in several aspects. A smart way to manage waste offers multiple practical advantages to formally optimise waste management processes. AI, ML, and IoT implementation in MSW management can significantly increase the effectiveness of garbage collection, transportation, and disposal efficiency (Ihsanullah *et al.*, 2022; Munir *et al.*, 2023). Through waste reduction, tracking, and streamlining management processes, these methods can help to mitigate the adverse effects on the environment.

AI can be applied to optimise waste collection routes and schedules based on historical data, real-time sensor inputs, and traffic patterns. Hence, fuel consumption can be optimized, thereby minimizing the environmental impact of waste collection. For instance, AI optimises renewable energy sources, improving energy efficiency and sustainability, and AI regulates energy usage in smart buildings, lowering costs and emissions (www.fdmgroup.com). Furthermore, AI enhances waste sorting processes by using computer vision to accurately identify and sort recyclable materials. This leads to higher recycling rates and reduced contamination of recyclables. For instance, robotics coupled with AI and ML have improved the quality of waste management processes (CleanRobotics, 2022). AI-powered sensors on waste bins can monitor the level of garbage and send signals when bins are nearing full capacity. This information helps optimise collection schedules, preventing unnecessary trips and reducing fuel consumption. Smart bins can also promote responsible waste disposal habits among the public. For instance, when someone throws or puts waste outside the bin, with the help of a sensor the smart bin gives the instruction not to throw the waste outside the bin (Vishnu *et al.*, 2021). AI can predict future waste generation patterns based on past data and external factors. This enables municipalities and waste management companies to anticipate peak times, plan resource allocation effectively, and ensure that collection services meet the demand, preventing overflow and environmental hazards (Kontokosta *et al.*, 2018). IoT-enabled sensors monitor the fill levels of waste bins in real time, allowing for just-in-time collection. Municipalities may minimise landfill utilisation, promote sustainability, reduce operational costs, and reduce GHG emissions by optimising collection routes and encouraging recycling and composting. IoT-generated data can be analysed to identify trends and patterns. Waste management authorities can use this information to make informed decisions, such as adjusting collection schedules, optimising resource allocation, and implementing targeted waste reduction initiatives. These results are very useful for policymakers, municipalities, and intelligent system developers in SWM. In this analysis, AI, ML, and IOT models are utilised to enhance the efficiency of the real-world needs of the waste management sector. Features such as precise waste bin monitoring, accurate trash forecasting, and optimised vehicle routing are critical features in terms of increased adaption rate. Successful integration of this method with existing systems requires strict compliance with environmental and data regulations. This analysis emphasises that the investments made in digital infrastructure should be prioritised and encourage the use of AI in MSW by governments and regulatory agencies. This would help in the amalgamation of intelligent approaches (AI, ML, and IoT), especially in developing countries, because in those countries limited resources are an obstacle to technological progress. Lastly, we recommend the implementation of public awareness campaigns and stakeholder engagement measures to strengthen the adoption of AI-based methods by waste management companies and communities to achieve sustainable waste management and additional benefits to society.

5.2 Strategies to overcome challenges

Adopting intelligent approaches in MSW faces several challenges, including high costs, data dependency, and infrastructure issues. These challenges require viable mitigation strategies to ensure the effective adoption of AI technologies. To mitigate high costs, public–private partnerships can help share investment burdens, while government grants and subsidies can provide essential funding (NSWAI, 2025). Cost can also be minimised with the help of authentic open-source AI tools and algorithms to reduce licensing and development costs. Leveraging open-source AI tools and adopting phased implementation strategies can also reduce expenses. For example, smart waste bins are very expensive compared with traditional bins so making their use widespread will be a problem. A possible solution for this problem would be the government funding these policies to reduce the price and make smart garbage bins affordable to the general public (Fang *et al.*, 2023). Addressing data dependency requires a multi-faceted approach that emphasises standardisation, technology, and collaboration (Shennib *et al.*, 2024). Establishing uniform protocols for data collection, annotation, and sharing across municipalities is a critical first step. IoT-enabled smart bins and sensors can provide real-time, consistent data to support these efforts (Anjum *et al.*, 2022). Collaborative data-sharing platforms among municipalities further enhance the quality and diversity of data available for AI training. Infrastructure barriers play a significant role in hindering the adoption of AI in SWM. Replacing existing infrastructure is challenging and resource-intensive. Therefore, it is essential to design new infrastructure in a way that allows for easy adaptation to evolving requirements. If implementing new setups involves high capital costs, stakeholders may hesitate to invest. To address this, a focus on modular and flexible infrastructure design is crucial, enabling customisation based on future needs with minimal cost and effort. This approach not only enhances adaptability but also ensures long-term sustainability, making the transition to AI-driven solutions more practical and efficient.

Excepting the challenges of high costs, data dependency, and infrastructure issues, the other critical factors in adopting intelligent approaches for SWM come with stakeholder engagement at the ground level. Integrating AI will necessitate input and buy-in from a wide array of stakeholders, from municipal officials and waste management workers to local communities and policymakers (Lakhouit, 2025). Capacity-building programs play a crucial role in enabling municipal workers to gain the skills needed for the effective operation and maintenance of AI systems (Lakhouit, 2025). To carry out such digital transformation in a company, educating them on the benefits of AI and the potential usage for innovation with the help of AI will help them to reduce the resistance towards change. The success of many AI-based waste management systems heavily relies on community participation. Awareness campaigns and incentives can motivate citizens to dispose of waste properly by segregating profitable waste from general waste and increasing public cooperation (P *et al.*, 2024). Another is providing incentive programs, such as discounts or rewards, to households that follow waste sorting guidelines guided by AI technology to promote its uptake (P *et al.*, 2024). More importantly, policymakers have a critical responsibility to establish a conducive regulatory framework that promotes the ethical implementation of AI and tackles issues related to data privacy and job loss. With aligning the goals of all stakeholders and a sense of collective accountability, the integration of AI can become a joint initiative and surmount the bottlenecks to make the way to the MSW management system sustainable and efficient.

6. Conclusions

In addressing the pressing challenge of urban waste disposal, the integration of intelligent technologies such as AI, ML, and the IoT in MSW management presents a transformative opportunity. However, as more people flock to urban centres, the basic system of waste management is not able to keep pace, calling for smarter solutions. The potential discussed in this paper highlights the crucial role that intelligent systems can play in minimising waste collection, sorting, and disposal, showing a pathway to environmental sustainability. This research demonstrates the ability of AI and ML to not only improve the accuracy of waste sorting methods but also increase operational efficacy by forecasting waste production cycles and organising collection paths. Adoption of these technologies will greatly lower fuel usage, decrease GHG emissions, and further recycling through improved separation. In addition, smart bins, enabled through the IoT technology, enable the real-time monitoring of waste levels and help municipalities implement just-in-time collection practices that better utilise resources.

Nevertheless, to ensure such cognitive solutions are fruitful, this must be done following their environmental regulations and solid data management practices. The search for commercialisation would, in turn, propel the need for digital infrastructure, which, if made available, would help emerging economies slip into places with access to AI and other similar technologies. Raising awareness and involving stakeholders will play an instrumental role in getting acceptance and encouraging sustainable actions. Intelligent approaches not only provide tangible solutions to pressing operational challenges; at the same time, they align with the quest for a more sustainable future. We educate people on how to adopt AI, ML, and IoT to establish efficient waste management systems to protect the environment and enhance urban life. This research has implications outside of academic discussions, providing actionable insights for waste management professionals and policymakers focused on promoting a sustainable future. This paper has some limitations that open up new opportunities for future researchers. This paper is mainly focused on articles and review journals, which makes the study limited. Therefore, the future researcher can explore the literature in a broad range. Apart from AI and ML, some other cutting-edge technologies, such as digital twins and blockchain, could be the subject of future research to create a more sustainable MSW system.

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