Journal of Environmental Management 373 (2025) 123658

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Review

Turning trash into treasure: Exploring the potential of AI in municipal waste management - An in-depth review and future prospects

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ARTICLE INFO

Keywords:
Artificial intelligence
Conceptual framework
Municipal waste
Optimization
Performance metrics
Systematic literature review

ABSTRACT

Rapid urbanization, economic expansion, and population growth have increased waste generation in many nations worldwide. Research on municipal waste management (MWM) is moving towards new frontiers in efficiency and applicability due to the growing amount of data being collected in these systems and the convergence of various technological applications; artificial intelligence (AI) techniques present novel and creative alternatives for MWM. Even though much research has been conducted in this field, relatively few review studies assess how advancements in AI techniques can contribute to the sustainable advancement of MWM systems. Furthermore, there are discrepancies and a dearth of knowledge regarding the operation of AI-based techniques in MWM. To close this gap, this study conducts a thorough review of the relevant literature with an application of preferred reporting items for systematic reviews and meta-analyses-based methods, examining 229 peer-reviewed publications to explore the role of AI in different MWM areas, such as waste characteristics forecasting, waste bin level monitoring, process parameter prediction, vehicle routing, and MWM planning. The main AI techniques and models used in MWM optimization, as well as the application areas and stated performance metrics, are all thoroughly analyzed in this review. A conceptual framework is proposed to guide research and practice to take a holistic approach to MWM, along with areas of future study that need to be explored. Researchers, policymakers, municipalities, governments, and other waste management organizations will benefit from this study to minimize costs, maximize efficiency, eliminate the need for manual labor, and change the approach to MWM.

1. Introduction

Rapid urbanization and population growth have led to an explosion in the worldwide population with the resulting generation of enormous amounts of waste (Zhang et al., 2024). A report published by the World Bank[1] projects an annual waste generation of 3.88 billion tonnes by 2050, an increase from 2.24 billion tonnes in 2020. Worldwide, approximately 43% of mismanaged solid waste is disposed of by incineration, open burning, illegal waste dumps, and unmonitored landfills (Andeobu et al., 2022a; Ihsanullah et al., 2022). The increased generation and composition complexity in MWM is widely acknowledged to have caused significant deterioration in public health, water quality, and air quality (Bhattacharya et al., 2024). These are also linked to climate change (e.g. methane gas release). Thus, one of the most significant and difficult problems facing the world today is effective and efficient MWM (Albizzati et al., 2024).

As a vital component of a contemporary city, MWM works to protect the entire ecological environment and prevent resource waste in

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[1] https://www.worldbank.org/en/topic/urbandevelopment/brief/solid-waste-management.

https://doi.org/10.1016/j.jenvman.2024.123658
Received 17 June 2024; Received in revised form 1 December 2024; Accepted 5 December 2024
Available online 9 December 2024
0301-4797/

Table 1
Synopsis of reviews of research on using AI techniques in MWM.

Reference	AI techniques	Number of articles	Period of study	Focus of study	Outcomes
Hoy et al. (2024a)	AI, ML, ANN, SVM, DT, GA	32	2013–2023	A systematic review of the use of artificial neural networks in municipal solid waste management to support low-carbon transition.	Artificial Neural Networks (ANNs) are widely used but unreliable in municipal solid waste management trend prediction.
Naveenkumar et al. (2023)	Multi-Layer Perceptron (MLP), DCNN, ANN, SVM, DT, GA, LR	N/A	N/A	A strategic review of AI, economic stability and life cycle assessment in municipal solid waste management and energy recovery.	AI-driven optimization promotes sustainable waste management practices and circular bioeconomy initiatives.
Ihsanullah et al. (2022)	SVM, DT, GA, RF, Multi-Layer Perceptron, ANN, CNN, RNN, Back Propagation, KNN, DNN, Particle Swarm Optimization	N/A	N/A	An overview of the literature on the most recent developments in AI applications for solid waste management.	AI techniques are increasingly used to enhance solid waste management processes, including generation, segregation, and treatment.
Andeobu et al. (2022a)	ANN, GA, DT, SVM, LR	197	2005–2021	A systematic review of applications of AI for sustainable solid waste management in Australia.	AI-based models outperform conventional methods in predicting waste generation and recycling, highlighting the need for upgraded recovery infrastructure.
Abdallah et al. (2020)	ANN, GA, LR, SVM, DT	85	2000–2020	A thorough review of the literature on the use of AI in solid waste management.	AI techniques exceed conventional methods in effectively modelling nonlinear processes and handling uncertainty in complicated solid waste management scenarios.
Our Study	ANN, SVM, GA, LR, DT, hybrid techniques	224	2010–June 2024	Although the aforementioned studies emphasize particular uses and challenges of AI in waste management, our research offers a thorough evaluation and a strategic framework for the broader integration of AI into MWM practices, addressing gaps and fostering sustainable development.	AI techniques offer innovative and sustainable solutions for MWM, improving efficiency in waste forecasting, monitoring, and planning.

addition to enhancing the quality of life for urban residents (Naveenkumar et al., 2023). The rapid growth in resource consumption and the increasing severity of environmental issues make it imperative to classify waste and apply appropriate treatments (such as composting, incineration, landfilling, recycling, and so on) for different types of waste (Pinhal Luqueci Thomaz et al., 2023). Waste should be sorted as soon as possible to maximize the amount of recycled materials and lower the likelihood of contamination from other waste materials (Qiang et al., 2024). Under the conventional MWM system, residents are in charge of sorting the garbage generated in their own homes. To ensure that waste is separated correctly at source, it is difficult to rely only on public awareness and publicity (Yoon and Lee, 2024). The entire MWM system may be rendered ineffective if citizens do not sort their waste following the source separation plan (Rafiquee and Shabbiruddin, 2024). Furthermore, the majority of conventional waste processing techniques, such as incineration and landfilling, are growing more costly and are energy-inefficient (Albizzati et al., 2024; Yoon and Lee, 2024). According to Wang et al. (2021), improper waste sorting can have a big financial impact on society. This expenditure is about 1.25 million USD annually for a medium-sized Swedish city like Borås. Even worse, an ineffective MWM system might lead to environmental contamination and harmful effects on future generations (Imran et al., 2024). Furthermore, the ability of conventional research methods, such as questionnaire surveys and simulation methods, to analyze waste-dumping behavior is limited due to the size of the population and the intricate nature of individual behaviors (Mor and Ravindra, 2023). This poses a difficult question in deciding how best to allocate funds for waste collection operations and the enhancement of regulations (Pinhal Luqueci Thomaz et al., 2023).

Considerable recent efforts have been made to shift the waste management industry toward sustainability and profitability through the application of innovative technologies and smart systems (Gupta et al., 2023; Naghibalsadati et al., 2024; Wang et al., 2024). It is anticipated that recently developed AI techniques will prove to be highly appropriate for application in the MWM field (Seyyedi et al., 2024). AI technology involves creating computer systems and programs that can emulate human characteristics, including problem-solving, learning, perception, comprehension, reasoning, and environmental awareness (Arashpour, 2023). AI techniques, including fuzzy logic (FL), genetic algorithms (GA), expert systems, and artificial neural networks (ANN), can configure complex mapping, solve poorly defined problems, and forecast outcomes (Wang et al., 2024). Every AI technique or algorithm has a distinct purpose; ANN models, for instance, can train data for prediction and classification (Ibrahim et al., 2024). Geographical analysis and big data handling in urban geography are also possible with ANNs (Tehrani et al., 2024). Expert systems, like FL, are not only knowledge-based but also capable of acquiring human cognitive abilities and reasoning (Siqueira et al., 2024). These systems are adept at handling complicated operations and qualitative characteristics thanks to their straightforward linguistic syntax (Mounadel et al., 2023). However, evolutionary algorithms, like GA, use natural selection as a model to choose the best-fitting data to deal with unforeseen circumstances and produce optimal results (Pourreza Movahed et al., 2020).

AI is gaining traction in the field of waste management, including predicting patterns of waste generation and optimizing waste collection routes, as well as locating and simulating waste management facilities (Ihsanullah et al., 2022; Behera et al., 2024). Review articles on AI research about particular waste-related application areas, like biogas production, waste combustion processes, petroleum waste management simulation and optimization, are scarce (Adeleke et al., 2021; Hu et al., 2024; Singh et al., 2024). To identify the gaps in existing literature, Table 1 gives a summary of earlier research reviews that investigate the application of AI in MWM settings. It also illustrates how this study's focus and outcomes differ from those of previous studies.

It is evident from Table 1 that no review article has been written that compiles all of the research on AI applications in the various areas of MWM. Thus, the application of AI techniques to MWM necessitates a thorough discussion about the current research and reported results to drive further advancements. To close this gap, this study conducts a thorough review of all literature to explore the role of AI techniques in different MWM areas (generation, collection, sorting, treatment, energy recovery, disposal, and waste management planning) based on the following research questions (RQs).

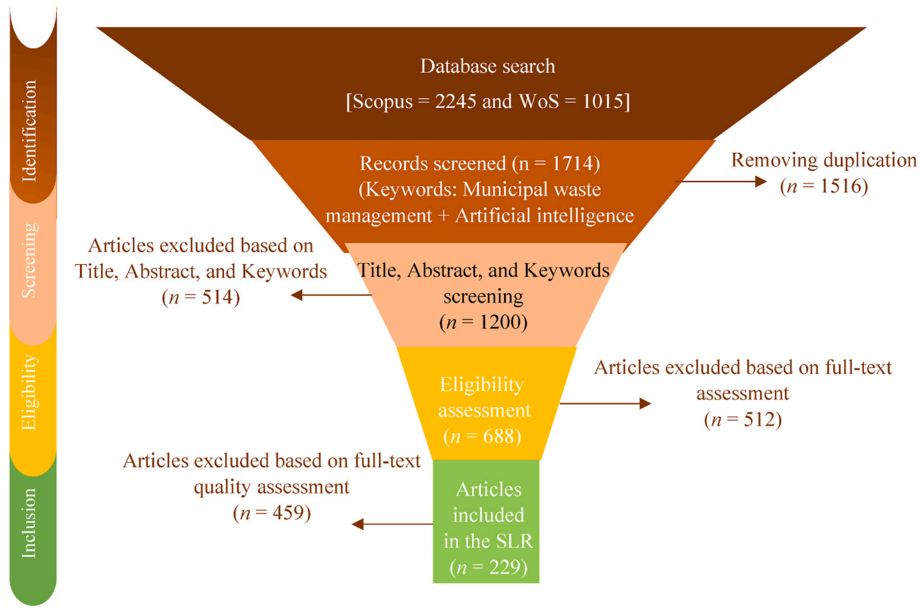

Fig. 1. Funnel diagram of SLRM using PRISMA guidelines.

RQ1. *What are the main AI techniques applied in MWM areas?*

RQ2. *In what ways does AI apply to the management of municipal waste?*

RQ3. *What opportunities and challenges exist for applying AI to the management of municipal waste?*

The study addresses the abovementioned research questions by conducting a systematic literature review along with a thorough analysis of AI techniques that can improve and revolutionize MWM systems. In taking such an approach, the purpose of this paper is threefold. Firstly, we seek to provide a thorough analysis of AI techniques that could improve and revolutionize MWM systems. Secondly, we examine the benefits and challenges of AI applications and suggest best practices to improve MWM system outcomes. Thirdly, we propose an integrative conceptual framework to guide research and practice to take a holistic approach to MWM. Lastly, areas of future study that need to be explored are discussed.

2. Review methodology

The objective of the present study is to examine the use of AI techniques in MWM by carefully examining previous research at the intersection of AI and MWM. This study aims to rectify the recognized shortcomings of the traditional narrative review approach (Tranfield et al., 2003). To achieve this, we implement an evidence-based (Mengist et al., 2020; Thomé et al., 2016) systematic literature review method (SLRM). This approach is becoming increasingly popular since it follows an extensive and exacting set of guidelines that make it easier to evaluate pertinent research that is easily accessible and applicable to a particular subject (Okoli and Schabram, 2010). Further, this approach makes it easier to identify research gaps in existing literature, opening up possibilities for additional research (Snyder, 2019).

Our contributions to the research phenomenon at the intersection of AI and MWM include finding, synthesizing, analyzing, interpreting, and reporting the distributed literature (into research flows). We develop a comprehensive framework that classifies the various types of AI techniques and the performance results of applying these techniques in MWM areas.

2.1. Locating studies

Finding a comprehensive list of essential contributions that minimize bias around the review questions is the goal of the journal article search and collection process (Tranfield et al., 2003). In line with earlier systematic reviews on waste management and AI (Soni et al., 2019; Abdallah et al., 2020; Andeobu et al., 2022a; Mounadel et al., 2023), four essential criteria are used to recognize pertinent studies that ensure the highest quality for the systematic literature review.

- *Database selection:* The search is conducted using the Web of Science (WoS) and Scopus databases. The Scopus electronic database includes a wide range of journals published by prominent publishers, including Elsevier, Taylor and Francis, IEEE, Emerald, and Springer (Kipper et al., 2020; Oliveira et al., 2018). The Scopus database is the most extensive and frequently updated searchable abstract and citation source for literature searches (Kipper et al., 2020). Scopus is selected over other databases for automated peer-reviewed article searching due to its wider coverage of peer-reviewed scientific publications (Oliveira et al., 2018; Vieira and Gomes, 2009) and notable overlaps with other databases such as WoS (Vieira and Gomes, 2009).
- *Time horizon:* Time horizon is used from a start date of 2010 based on the findings of the pilot search. While research on the convergence of AI and MWM predates 2010 (e.g. Al-Jarrah and Abu-Qdais, 2006), the period since marks a notable transition towards the use of advanced AI techniques, including machine learning and neural networks (Abu Qdais et al., 2010), which have subsequently evolved into vital components for improving waste management practices. As such, starting our study in 2010 allows us to focus on the most relevant and crucial breakthroughs that have shaped the current landscape of AI in MWM, thereby offering a more accurate portrayal of the continuous growth in this area.
- *Journal selection:* We only include scientific papers in the English language in the subject area that are published in peer-reviewed scholarly journals to guarantee the calibre of our systematic literature review (SLR). Peer review is a quality indicator that makes it possible to evaluate the conceptual and methodological rigor of studies, improving the technical product. Scholarly publications that undergo peer review are seen to be of a higher calibre than those that do not.
- *Keywords selection:* Authors then agree on a selection of search keywords based on a combination of conversations with academics and a review of the relevant literature. The search string is designed using

Boolean operators as a combination of two-word groups. The first group of keywords is associated with AI; this consists of “Artificial intelligence,” “AI,” “machine learning,” “deep learning,” “neural networks,” intelligent systems,” “data analytics,” “big data,” and “simulation”; the other group of keywords related to MWM includes “municipal waste management,” “municipal solid waste,” “waste disposal,” “waste treatment,” “landfill management,” “waste generation,” “waste collection,” “waste sorting,” “resource recovery,” “waste minimization,” and “waste management planning”. The Boolean operator “OR” is used to combine the keywords within the same group; “AND” is used to combine the two main groups of keywords related to both AI and MWM. The initial search yields 1771 results in Scopus and 937 in WoS.

2.2. PRISMA flow diagram

The SLRM is used in this study as a methodological framework to examine and compile previous research on the application of AI in MWM, focusing on advancements in AI techniques in MWM systems performance. The SLRM follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (see Fig. 1), acclaimed for their comprehensive reviewing process (Page et al., 2021). The PRISMA-based method for SLRM helps to guarantee the review’s quality. It enables readers to evaluate its advantages and disadvantages, allows review methods, the structure and format of the review to be replicated using PRISMA; it serves as a resource for other experts in the field. The PRISMA method provides accurate data for future research because it makes sure even obscure details cannot be overlooked; it also outlines the information flow through the different steps of the systematic literature review (i.e. identification, screening, eligibility, inclusion) (Moher et al., 2009).

The final sample is developed by identifying, screening, and evaluating articles for eligibility after inclusion and exclusion criteria are established (see Section 2.1). An overview of the PRISMA-based systematic review approach is presented in Fig. 1. Following the identification process, a total of 3260 articles are identified from selected electronic database searches. After duplicates are removed, 1714 papers remain. During the screening stage, two researchers independently examine the studies acquired in the previous stage to ensure robustness. Subsequently, articles are excluded based on their titles, abstract content, and duplication. To do so, we first read the article titles, thus screening 514 articles unsuitable for the study, considering the research aim and questions. As a result, 1200 papers are forwarded for abstract review, checked for compatibility with the study’s objective and research questions, with those deemed unsuitable, manually evaluated and screened. As a result, 512 articles are eliminated. In the eligibility phase, a full-text analysis of 688 articles is conducted considering several criteria (i.e. Are AI techniques and MWM addressed together in the article? Does the article have a management focus? Are AI techniques or MWM the main topic of the article?). Finally, a full-text quality assessment screening is carried out, taking into account the publication’s scientific rigor in addition to its topical relevance. While several publications that do not fit our topic requirements are detected during this phase, the main reason for rejecting the articles at this stage is the critical evaluation of the validity of the methodology of the authors alongside the degree of generalizability and confidence in the claims. Thus, 229 articles with the required qualification criteria remain for further analysis. All 229 articles selected in the previous step of SLR are thoroughly evaluated using content analysis to yield results in line with the proposed research questions. The results of the content analysis serve to address the research questions and the development of a framework to map the role of AI techniques in different MWM areas.

2.3. Data analysis

Analyzing and synthesizing the research requires selecting the best method and definitions. A variety of methods are considered for the research synthesis, including thematic analysis/synthesis with meta-cognitive mind maps, qualitative comparative analysis, meta-summaries, and content analysis (Vaismoradi et al., 2013; Bengtsson, 2016; Mengist et al., 2020). A descriptive analysis is chosen for this study as it does not infer the effect of human beings and allows a variety of research data and statistics to be elaborated and demonstrated, thus giving the study a more quantitative character (Vaismoradi et al., 2013). An Excel database is used to analyze the following data for each article: authors, title, journal, publication year, document source, findings, AI techniques addressed and used, and MWM applications area. At this stage, structures have to be pre-defined to collect the required information needed to explore each article’s essential and relevant details (Thomé et al., 2016; Tranfield et al., 2003). Following this, we conduct a content analysis to uncover the major spectrums and themes found in all of the articles reviewed. As such, with the help of descriptive and content analysis, we are able to produce a comprehensive review by combining our ideas and exploring any unresolved but crucial topics.

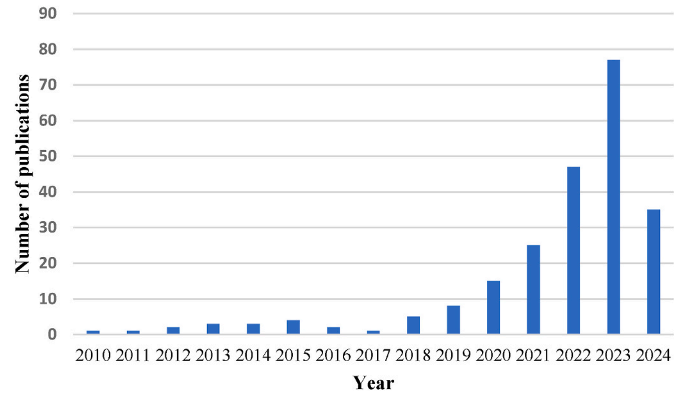

Fig. 2. Number of publications per year.

2.3.1. Coding strategy

Using a hybrid coding strategy, both deductive and inductive methods are used to analyze the data (Azungah, 2018). In deductive coding, predefined codes are applied based on prior research and existing theories regarding AI and MWM. As a result of these predefined codes, it is possible to identify patterns and themes within the literature in a structured manner. Simultaneously, inductive coding is utilized to enable new themes and patterns to emerge directly from the data itself, ensuring that the analysis captures novel perspectives beyond what is expected from previous studies (Pacheco-Romero et al., 2021).

The coding process is conducted as follows. Firstly, we begin by reviewing the selected studies and applying the predefined codes derived from relevant literature on AI and MWM. During this deductive phase, the established themes - AI techniques and MWM application areas - are categorized. Secondly, we conduct a thorough examination of the data independently of the predefined codes. Throughout this phase, we identify emerging themes that had not been previously considered, such as the role of AI in addressing MWM challenges and its applications to MWM. Finally, we combine these records with integrated deductive and inductive codes into a complementary framework. This step ensures a thorough analysis that includes both existing knowledge and new insights.

3. Results

This section presents the findings from the literature review. To produce new knowledge and perspectives regarding the research topic at the intersection of MWM and AI, the analysis process takes into consideration the research methodology outlined in Section 2 (Thomé et al., 2016; Tranfield et al., 2003) that was not evident from reading the

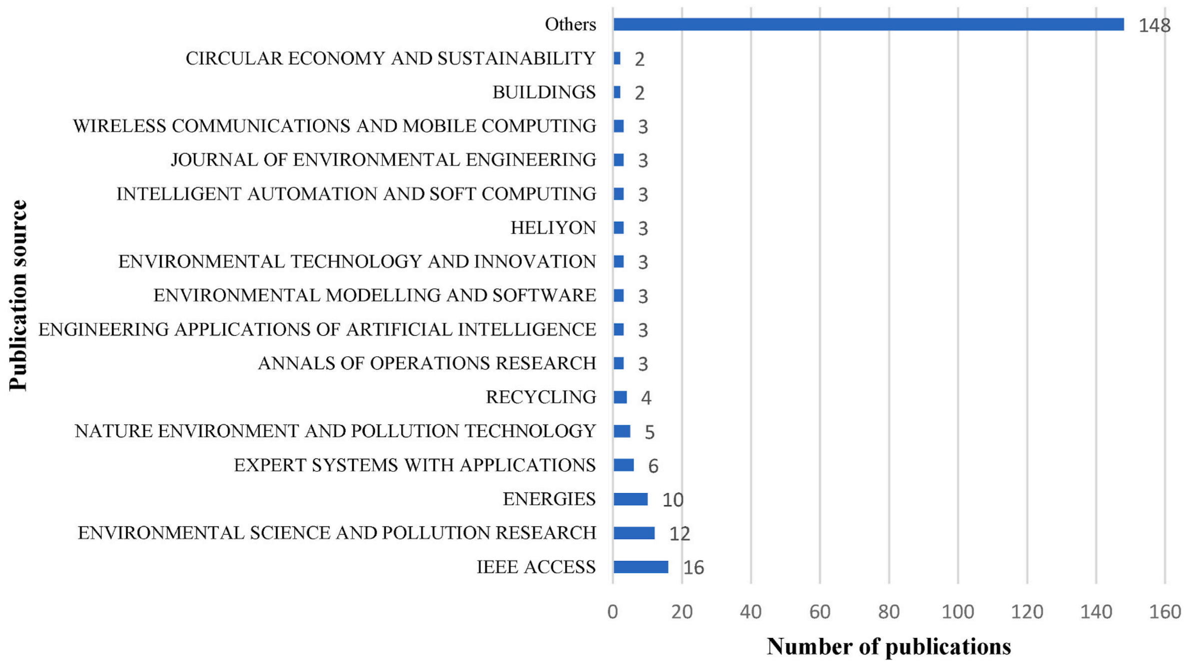

Fig. 3. Journal-wise publications (n = 229).

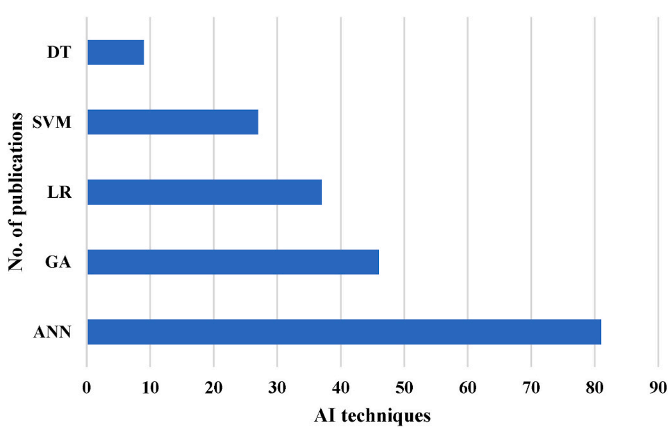

Fig. 4. Publications distribution by the main AI techniques used.

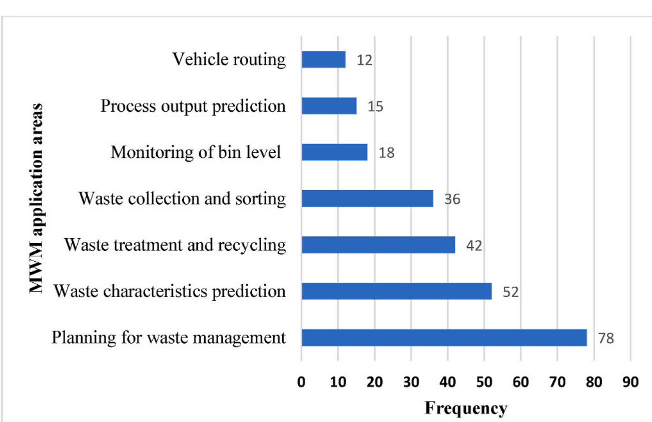

Fig. 5. Number of studies according to MWM application areas.

individual articles. The gaps from this extensive review are then used to propose future research directions.

3.1. Descriptive analysis

We find that 229 pertinent publications address our area of interest; 83% of these were released in the last five years, indicating the recent increase in scholarly interest. Fig. 2 illustrates the increasing interest among academic researchers in examining the role of AI in MWM; this could be attributed to ongoing developments in AI applications and relevant techniques in MWM. The number of articles increases gradually from one in 2017 to five in 2018, then sharply to 77 from 2019 to 2023. The fact that there are only 35 relevant articles found in 2024 might suggest a drop, but as the year is only six months old, the number is likely to increase.

There are 149 peer-reviewed, multidisciplinary academic journals that publish the 229 articles on our shortlist. The outcome highlights the topic's interdisciplinary nature. Fig. 3 shows the source relevancy: IEEE Access (16 articles; 7%); Environmental Science and Pollution Research (12 articles; 5%); Energies (10 articles; 4%); Expert Systems with Applications (6 articles; 3%); and Nature Environment and Pollution Technology (5 articles; 2%).

Artificial neural networks (ANN), support vector machines (SVM), linear regression (LR), decision trees (DT), and genetic algorithms (GA) are found to be the most widely used AI techniques for the modelling and optimization of MWM systems, as shown in Fig. 4 of the literature review. The literature uses a range of ANN algorithms, such as multi-layer perceptron (MLP), feed-forward, autoregressive, recurrent, and radial basis functions (RBF). ANNs are the most popular AI technique used in the realm of MWM (81 articles; 35%). GA is the second most AI technique used (46 articles; 20%), followed by LR (37 articles; 16%) incorporating multiple and multivariate LR and gradient-boosting regression. Several models are employed less frequently in individual studies, including logistic model tree, Q-type clustering, ant colony optimization (ACO), wavelet transform (WT), K-means, data mining, Naïve Bayes, rough sets, artificial immune system (AIS), random forest (RF), and adaptive neuro-fuzzy inference systems (ANFIS).

In addition, we create a graph showing the different MWM areas where AI-based techniques are applied to enhance MWM performance.

Waste management planning (78 articles; 35%), waste characteristics prediction (52 articles; 23%), waste treatment and recycling (42 articles; 19%), waste collection and sorting (36 articles; 16%), bin level monitoring (18 articles; 8%), process output prediction (15 articles; 7%), and vehicle routing (12 articles; 5%) are the main application areas for AI-based MWM. While bin level monitoring is connected to tracking how full waste bins are, waste characteristics prediction encompasses waste material classification, waste compression rate, waste production trends, or patterns. Waste composition analysis and route optimization are included in the waste collection and sorting process. Waste-to-energy conversion and the oversight and management of landfill operations are included in the waste treatment and disposal process. Waste management planning includes the location of waste facilities, the positions of waste accumulation areas and illegal disposal sites, and the optimization of the financial and environmental effects of collection, transportation, treatment, and disposal. The objective of the vehicle routing problem is to optimize the routes and frequency of waste collection. Finally, the process output prediction includes leachate formation and biogas generation simulation and optimization. The total number of publications carried out in each MWM application area over the assessment period is shown in Fig. 5.

4. Content analysis

In this study, secondary data from the systematic literature review of earlier studies is analyzed using content analysis. The goal of content analysis is to arrange and analyze the information gathered to make best decisions (Bengtsson, 2016; Vaismoradi et al., 2013). A content analysis of the articles reveals the themes and keywords in each relevant article. The following subsections define the AI techniques used in MWM areas to help with the discussion that follows.

4.1. AI techniques

Solid waste prediction and optimization are two areas in which researchers employ AI-based techniques (Ihsanullah et al., 2022; Seyyedi et al., 2024). MWM seeks to maximize several processes involved, including waste identification, collection, best location for trash bins, shortest routes for transportation, and disposal.

In recent years, the increasing investment in AI solutions by governments and organizations across diverse sectors has led to a surge in the adoption of AI techniques (Mounadel et al., 2023). The waste management and recycling industry, like many other industries worldwide, is attempting to take advantage of the opportunities that AI techniques present to improve its waste management strategies (Andeobu et al., 2022a; Mounadel et al., 2023). After reviewing previous research, it can be seen that the following five AI techniques are the most commonly used for modelling and waste management process optimization: (a) ANNs (b) DT (c) SVM (d) GA and (e) LR. These AI techniques, along with their benefits and challenges, are covered in the following sections.

4.1.1. Artificial neural network

Multiple variables are involved in MWM processes, and because of their non-linear behavior, modelling these processes can be challenging. ANNs work well for modelling processes with partial or ambiguous data sets and for handling difficult and imprecise tasks that call for human judgment (Hoy et al., 2024a). Numerous ANN algorithms, including feed-forward autoregressive, multi-layer perception (MLP), radial basis function (RBF), backpropagation (BP), and recurrent ANNs, are applied to waste management (Abbasi and El Hanandeh, 2016; Ihsanullah et al., 2022). Neural networks typically consist of three layers - an input layer, hidden layers, and output layers. Each layer consists of several nodes connected by directed weighted edges, and each layer node is linked to each sub-layer node (Ayeleru et al., 2021). Energy recovery, co-melting temperature of waste, leachate formation, biogas generation, waste classification, bin level status, heating value, and ideal waste collection routes are among the areas where ANNs have proven to be effective (Adamović et al., 2018; Liang et al., 2021; Shahbaz et al., 2019). Because of their resilience to failure, robustness, and the ability to represent the intricate relationships between variables in multivariate systems, ANNs are also extensively utilized to model a range of waste management processes (Abbasi and El Hanandeh, 2016). Furthermore, ANN systems are preferable in those scenarios because they typically require fewer parameters for calibration than deterministic models (Almomani, 2020; Cho et al., 2021). However, ANNs are prone to overfitting but are useful in solving high-accuracy arithmetic and logical problems (Ayeleru et al., 2021). Furthermore, the relative importance of the various factors under analysis - that is, the input characteristic that has the largest influence on the output - cannot be ascertained by ANNs (Mounadel et al., 2023).

4.1.2. Support vector machines

Supervised non-parametric algorithms for statistical learning are called SVMs (Zhu et al., 2019). SVMs were first developed to address classification issues. Still, due to their superior performance over several traditional regression techniques, they have since been used to address regression issues as well (Zhang et al., 2023a). Unlike statistical techniques like principal component analysis (PCA), which only deal with the model's dimensionality, support vector regression algorithms are less likely to overfit and are adept at lowering error estimates and model dimensions at the same time (Dai et al., 2011). SVMs offer simple solution analysis and are inexpensive in terms of computation and generalization errors (Ayeleru et al., 2021). SVMs are, nevertheless, extremely susceptible to tuning and kernel-selected variables (You et al., 2017). However, it is shown that a SVM is especially useful for forecasting waste heating value, waste classification, waste generation, and energy recovery (Hata et al., 2015; Altin et al., 2023; Liu et al., 2020).

4.1.3. Genetic algorithm

Genetic algorithms are a class of metaheuristic search algorithms that imitate spontaneous evolution (Pourreza Movahed et al., 2020). Natural selection and genetics are used by genetic algorithms to solve problems (Buenrostro-Delgado et al., 2015). These algorithms are more intelligent than random search algorithms because they use past data to focus the search on the highest-performing area of the solution space (Yılmaz et al., 2022). Fittest selection, crossover, and mutation are the three primary elements of genetic algorithms (Xue et al., 2021). Crossover is the process of moving data between two strings, each of which represents a binary or decimal solution, as opposed to mutation, which involves flipping specific string digits to produce new solutions (Alsulaili et al., 2024). By contrasting each generated solution with the optimization problem's objective, the overall fitness of each solution is evaluated. The best answers are then chosen for the ensuing optimization procedure (Kuo et al., 2012; Xi et al., 2013). GAs have been widely used to solve waste management issues, such as waste classification, forecasting of waste generation, prediction of waste accumulation and facility siting, and estimation of the value of waste heating and biogas generation (Biglarijoo et al., 2017; Jacob and Banerjee, 2016; Rabbani et al., 2018). They are also helpful in minimizing the effects of waste handling on the environment, management expenses, and collection routes (Pourreza Movahed et al., 2020). However, GAs require careful construction and are not useful for solving simple problems since an incorrect choice of operators could negatively impact the model's outputs (Liang et al., 2021; Pinhal Luqueci Thomaz et al., 2023).

4.1.4. Decision trees

Another well-used AI technique in MWM is the decision tree (Ding et al., 2023). DT is a well-performing supervised classification method that can extract rules from unidentified data (Kannangara et al., 2018). It is especially helpful for expert systems which can generate outcomes that are comparable to those of a human expert in a given field (Johnson et al., 2017). Aside from being able to handle data with missing values

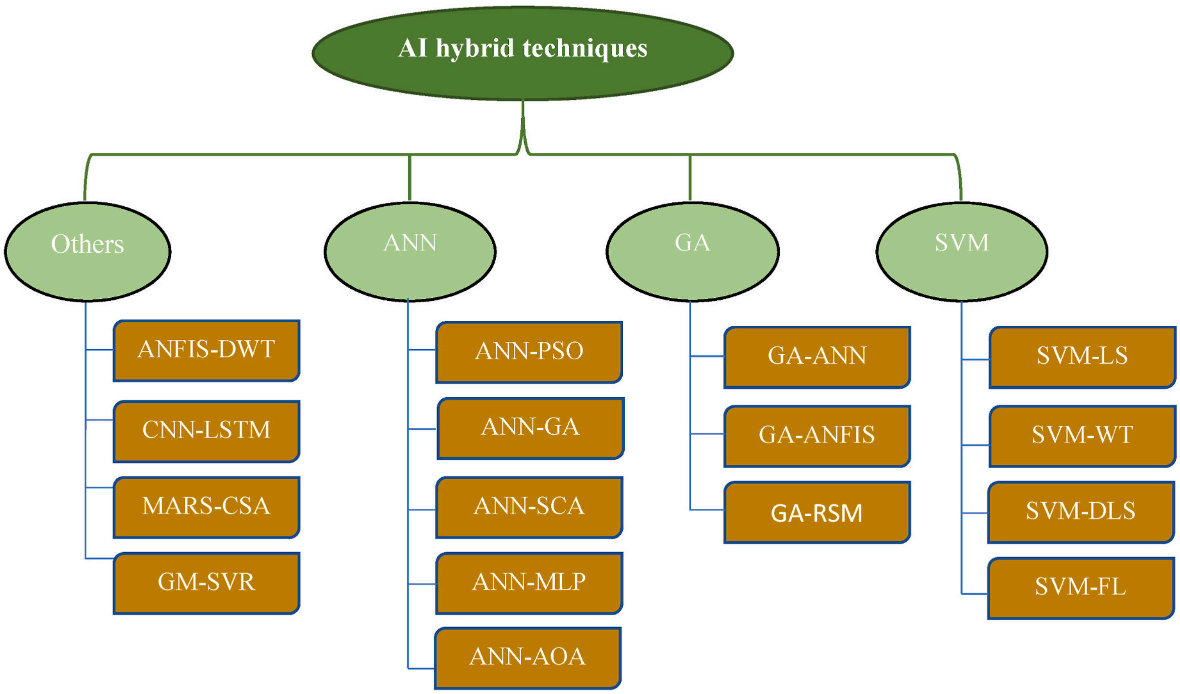

Fig. 6. Classification of AI hybrid techniques for forecasting and predicting the generation of municipal waste.

and irrelevant features, DTs also have the advantage of producing easy to interpret results and having low computational costs (Deepnarain et al., 2019; Xia et al., 2022). Nevertheless, there is a risk of data overfitting with this technique (Mounadel et al., 2023; Pinhal Luqueci Thomaz et al., 2023). DTs have been used in MWM to predict waste generation, waste compression, and waste classification. They have also been used to identify areas where waste is illegally dumped and patterns in the generation of waste (Kannangara et al., 2018; Deepnarain et al., 2019; Ding et al., 2023).

4.1.5. *Linear regression*

LR analysis is a supervised method that uses independent predictors to model a desired value (Ghinea et al., 2016). One variable (simple linear regression) or multiple variables (multiple linear regression) can be used to illustrate MWM models (Azadi and Karimi-Jashni, 2016). Since MWM models typically depend on multiple parameters, multiple (or multivariate) LR is a better fit for predicting these MWM processes (Chu et al., 2022). The key advantages of utilizing LR are its low computational costs and simple result interpretation (Ho Park et al., 2021; Ezzahra Yatim et al., 2022). However, it is generally accepted that modelling non-linear data is inappropriate for this technique (Cho et al., 2021; Wilts et al., 2021). LR is frequently used in the field of MWM to forecast leachate formation and waste generation (Ghinea et al., 2016). It has also been used to maximize the frequencies and routes of waste collection (Chu et al., 2022).

4.1.6. *Hybrid techniques*

Hybrid techniques aim to overcome the limitations of implementing those systems independently by combining various AI techniques with metaheuristic algorithms or each other. The goal of hybrid or ensemble techniques is to improve base regressor and classifier predictive performance by merging intelligently weak learners (Abdallah et al., 2020; Cha et al., 2022). In comparison to individual AI techniques, hybrid techniques perform better (Ihsanullah et al., 2022; Lin et al., 2022). Researchers combine ANN with SCA, GA, MLP, and recurrent sparse memory (RSM) to improve the prediction accuracy of municipal waste generation (Kuo et al., 2012; Liang et al., 2021; Ayeleru et al., 2021). In a similar vein, SVM combines with deep learning-based segmentation (DLS), wavelet theory (WT), federated learning (FL), and computer vision for e-waste management (Lu et al., 2022; Majchrowska et al., 2022; Selvakanmani et al., 2024). Lin et al. (2021) predict the production of municipal solid waste using CNN with Long Short-Term Memory (LSTM), while Liang et al. (2021) predict municipal solid waste flow using ANN combined with sine cosine algorithm (SCA), the Archimedes optimization algorithm (AOA), the particle swarm optimization (PSO) technique, and GA. Fig. 6 illustrates the AI hybrid techniques used in forecasting and prediction of the generation of municipal waste.

4.2. *AI application areas in municipal waste management*

Municipal waste is currently managed through the use of landfills, incinerators, composting, and recycling. These MWM practices are currently thought to be a major contributor to the climate crisis, involving several environmental and health issues (Abdallah et al., 2020; Tao, 2024). Furthermore, several categories of municipal waste are complicated, expensive to recycle, labor-intensive, and directly endanger the health of municipal waste workers who handle waste collection and disposal (Cha et al., 2022; Lin et al., 2021). In light of this, the use of AI techniques is altering the way that technological intervention is used to manage municipal waste. The systems used in generation, collection, sorting, transportation, and recycling of solid waste are being impacted by AI-driven MWM initiatives (Lin et al., 2021, 2022). With the application of AI techniques, conventional recycling and decomposition methods become more practical and efficient (Ihsanullah et al., 2022; Soni et al., 2019). Table 2 illustrates and discusses specific applications and key outcomes of AI techniques in different MWM areas.

4.2.1. *Waste characteristics prediction*

One of the essential components of an effective waste scheduling design and implementation is the estimation of municipal waste. As a result, forecasting municipal waste helps to design a strategy for collection, storage, and vehicle routing (Ghinea et al., 2016). It also helps to establish a waste treatment system and suggests opportunities for recycling and recovery (Soni et al., 2019). Accurately estimating the rates of municipal waste helps with site development, policy

Table 2
Summary of AI techniques applications in MWM.

MWM Application Area	AI Technique	Pre-determined Parameters	Specific Application	Key outcomes	References
Waste Management Planning	ANN	Spatial data (e.g. location, terrain) Population density Historical waste records	Illegal dumpsite detection	Using geographic data to reduce environmental risks, enhance surveillance, and forecast the potential of illegal dumping.	(Azadi and Karimi-Jashni, 2016; Jacob and Banerjee, 2016; Chu et al., 2022; Ezzahra Yatim et al., 2022)
	DT	Waste generation rates Population growth Collection frequency	Waste accumulation forecasting	Identifying waste accumulation patterns and offering practical advice for building future waste management infrastructure.	Ding et al. (2023)
	LR	Historical costs Population size Waste volume	Cost management strategies	Developing linear models based on past data to forecast waste management expenses, helping to decrease costs associated with municipal services.	Dashti et al. (2021)
	GA	Waste processing capacity CO2 emission limits Operational costs	Environmental impact optimization	Minimizing carbon emissions and environmental damage through the optimization of waste management decisions and the identification of the most environmentally friendly options.	Jacob and Banerjee (2016)
	SVM	Waste types Environmental impact data Distance to disposal sites	Environmental impact analysis	Locating high-impact zones and forecasting the environmental dangers of waste management systems.	(Hata et al., 2015; S. Zhang et al., 2023a)
Process Output	ANN	Organic waste input Environmental conditions (e.g. temperature) Biogas output	Biogas production prediction	Precisely predicting the amount of biogas generated during the breakdown of organic waste, increasing the effectiveness of renewable energy production.	(Almomani, 2020; Cho et al., 2021)
	DT	Waste type Weather conditions Leachate generation potential	Leachate generation categorization	Optimizing landfill management techniques by categorizing different waste types and conditions according to their ability to produce leachate.	(Yılmaz et al., 2022; Gaur et al., 2024)
	LR	Waste moisture content Precipitation levels Waste type	Leachate generation estimation	Estimating the amount of leachate generated from various waste types using past data to support waste water treatment procedures.	(Ho Park et al., 2021; Chu et al., 2022)
	GA	Organic waste type Decomposition rate Biogas conversion efficiency	Optimizing biogas production	Optimizing waste-to-energy conversion systems and fine-tuning parameters to maximize biogas generation from waste materials.	Sun et al. (2024)
	SVM	Waste types Leachate composition Environmental factors	Leachate production prediction	Enabling more precise management of landfill effluent through the classification of waste types according to their potential for leachate generation.	(Ayeleru et al., 2021; Gaur et al., 2024)
Waste Bin Management	ANN	Bin usage patterns Collection intervals Bin capacity	Bin level status prediction	Optimizing collection schedules by estimating the point at which bins will be filled using past usage data.	(Ayeleru et al., 2021; Hoy et al., 2024b)
	SVM	Bin location Waste type Fill level thresholds	Bin status classification	Classifying bin fullness levels to improve garbage collection efficiency and lower overflow incidences.	Zhu et al. (2019)
Waste Characteristics	ANN	Waste composition Environmental data Historical waste generation	Waste generation forecasting	Improving long-term planning by forecasting future trash generation rates through the analysis of environmental and historical data.	Hoy et al. (2024a)
	DT	Waste type Physical properties Hazard levels	Waste categorization	Sorting garbage more efficiently by dividing it into separate categories (e.g. organic, plastic) according to its physical characteristics.	Abu Qdais et al. (2010)
	LR	Waste type Moisture content Calorific value	Heating value estimation	Assisting in the decision-making process for waste-to-energy facilities by modelling correlations between waste type and heating value.	(Ding et al., 2023; Hoy et al., 2024a)
	GA	Compaction force Waste type Energy consumption	Optimizing waste compaction	Reducing the amount of garbage dumped in landfills by fine-tuning compacting machine parameters to enhance waste density.	Nowakowski et al. (2018)
	SVM	Waste type Physical properties Sorting thresholds	Waste categorization	Enhancing the effectiveness of waste sorting procedures by categorizing different types of waste according to their physical and chemical characteristics.	Zhu et al. (2019)
Waste Collection and Sorting	ANN	Waste composition Recyclable materials Recovery facility capacity	Material recovery facility optimization	Enhancing facility capacity and efficiency by predicting the amount and quality of recyclables retrieved.	Shahbaz et al. (2019)
	DT	Waste stream Sorting cost Recyclable value	Material classification in recovery facilities	Classifying various waste streams (e.g. plastics and metals) to increase the effectiveness of sorting in material recovery facilities (MRFs).	Pourreza Movahed et al. (2020)

(continued on next page)

Table 2 (*continued*)

MWM Application Area	AI Technique	Pre-determined Parameters	Specific Application	Key outcomes	References
	SVM	Recyclable types Sorting thresholds Recovery efficiency	Resource recovery classification	Reducing contamination in recovered materials, increasing sorting precision, and accurately identifying recyclables.	2015; Zhang et al. (2023)
Vehicle Routing	ANN	Collection route data Traffic conditions Fuel consumption rates	Collection route optimization	Optimizing fleet efficiency by reducing fuel usage and recommending the best collection routes based on historical route data.	(Xi et al., 2013; Buenrostro-Delgado et al., 2015; Jacob and Banerjee, 2016)
	DT	Waste volume Traffic density Collection points	Route selection for waste collection	Enhancing collection efficiency by categorizing routes according to garbage levels and traffic patterns.	Yang et al. (2018)
	GA	Collection points Fuel consumption Traffic patterns	Optimizing collection route planning	Identifying the best collection routes to reduce fuel usage and collection times, hence increasing fleet productivity.	Azadi and Karimi-Jashni (2016)
	SVM	Waste type Route distance Traffic patterns	Collection route classification	Organizing routes into distinct groups according to factors such as traffic, waste nature, and distance, offers valuable information for optimizing waste collection scheduling.	(Chu et al., 2022; Ezzahra Yatim et al., 2022)

implementation, environmental degradation mitigation, and disposal technique selection (Singh et al., 2024). Before decision-makers take any further action, generating less waste can be achieved by using AI techniques to predict municipal waste rates (Ayeleru et al., 2021). However, relying solely on conventional statistical forecasting methods will not allow for the efficient prediction of municipal waste and the full realization of the task's benefits (Munir et al., 2023). Widespread inefficiencies in the management of municipal waste are primarily caused by imprecise and inaccurate forecasting (Cha et al., 2022; Majchrowska et al., 2022). Although there are a variety of approaches to forecasting the generation of solid waste, they can be broadly divided into five groups: AI methods, time series analysis, material flow methods, regression analysis, and descriptive statistical models (Ho Park et al., 2021; Johnson et al., 2017). AI-based techniques are better predictors than other approaches regarding the generation of solid waste (Azadi and Karimi-Jashni, 2016; Zhu et al., 2019). For example, ANNs are extensively used as they can accurately anticipate waste generation, composition, and recycling potential by modelling complicated, nonlinear relationships in waste composition (Ibrahim et al., 2024). In contrast, SVMs provide excellent accuracy in classifying waste materials based on their chemical and physical characteristics, facilitating effective sorting and recycling operations (Zhang et al., 2023b). Further, LR is an effective technique for modelling linear correlations between waste generation and socioeconomic or demographic parameters; this helps in identifying the variables that affect waste production patterns (Ezzahra Yatim et al., 2022).

4.2.2. *Bin-level monitoring*

Effective bin-level monitoring is required because inappropriate municipal waste disposal puts public health and the environment at risk (Johnson et al., 2017). Large cities have a lot of trash bins that are overflowing due to outdated and typically ineffective waste disposal practices (Andeobu et al., 2022a). Nowadays, audits and observations are conducted on less than 1% of trash bins (Wang et al., 2021). This costly manual process has limited insights into effective MWM and is challenging to measure. In light of this, real-time solid waste flow analysis is provided by AI-based techniques which boost productivity and lower risks in recycling facilities (Yılmaz et al., 2022). A smart AI-based MWM monitoring system can maximize real-time information regarding bin level status and bin location/position based on their current state (Selvakanmani et al., 2024). For instance, Rahman et al. (2022) create and evaluate an autonomous Internet of Things system that uses an AI-based model from a central monitoring station to track waste bins' empty levels. The developed system produces high-accuracy (98.5%) results and is successful in bin-level status prediction. According to Almomani (2020), collecting data from smart sensors in waste bins is a common application for ANNs; they can forecast fill levels based on past trends and real-time inputs. Using sensor data inputs, SVMs are used to classify waste bin status - full, half full, or empty - helping to improve the precision and efficiency of waste collection operations (Zhu et al., 2019). According to Ezzahra Yatim et al. (2022), LR models offer a simple method of estimating bin full levels by developing linear correlations between waste generation rates and variables including location, density, and time of day. Further, DTs are used to create decision rules for real-time bin status monitoring, enabling waste management operators to see trends in waste production and adjust resource allocation appropriately (Meza et al., 2019).

4.2.3. *Waste classification*

The task of classifying waste is regarded as an efficient means of treating and disposing of waste. Sorting waste into different categories will help to decide on landfill or incinerate in addition to the recycling process (Ihsanullah et al., 2022). Furthermore, recycling waste is crucial for a sustainable society because it cuts down on waste production (Zhang et al., 2023a). Currently, several studies offer intelligent waste recognition and classification techniques that enable waste images to be automatically sorted. These techniques are meant to tackle the challenging issues that come with manually sorting waste, like high workloads, human error, and low sorting efficiency (Chen et al., 2021; Lin et al., 2022; Yılmaz et al., 2022). These methods can also help to lower labor costs, preserve human resources, and increase the rates at which resources are reused (Dai et al., 2011). The field of computer vision and AI has advanced at a rapid pace, making it possible to identify and recognize waste from images automatically (Lu et al., 2022). Eventually, this will take the place of manual sorting. Recently, CNNs have been positioned as the most widely used technique for image recognition (Lin et al., 2021). However, because CNN performance is dependent on the information extracted from the image, inadequate image features will negatively impact the classification outcomes (Liang and Gu, 2021). CNNs and an AutoEncoder structure are combined in a waste classification method presented by Toğaçar et al. (2020). By utilizing a publicly available dataset divided into two categories (recyclable and organic waste), the accuracy of the model was tested and found to be 99.95%. A multilayer hybrid CNN-based vision transformer for waste classification is presented by Alrayes et al. (2023). This model separates waste into recyclables and non-recyclables to extract features from images. The outcomes showed that the hybrid system could achieve a maximum accuracy of 98.2%. Furthermore, the majority of research employing DL-based methods for waste classification improperly assumed that each image contains only one type of waste (Zhang et al., 2023b). To simultaneously identify and locate different waste items in the picture, Liang and Gu (2021) propose a deep CNN to simultaneously localize and recognize waste types in pictures. With an accuracy of 97.16%, the model performs remarkably well on all evaluation metrics.

4.2.4. Route planning, waste collection, and vehicle routing

An efficient solid waste collection procedure is necessary for an integrated MWM strategy to be successful (Lin et al., 2021). For many municipalities, waste collection usually makes up between 70 and 85% of all MWM costs (Kannangara et al., 2018). Inadequate truck allocation and disorganized collection schedules lead to unnecessary delays and traffic jams in addition to raising operating costs (Rahman et al., 2022). Hence, in addition to the continuous development of smart waste collection technology, new approaches for AI-based smart waste collection need to be created and put into practice (Liang and Gu, 2021; Toğaçar et al., 2020). A review of literature reveals that the use of AI-based methods for collecting solid waste has only been examined in a very small number of studies (see Table 2). Most of these studies concentrate on using ANN, GA, and LR to optimize waste collection frequency and route planning models (Liang and Gu, 2021; Selvakanmani et al., 2024). For instance, Vu et al. (2019) integrate a geographic information system (GIS) waste collection route optimization tool with an ANN waste prediction model. The study demonstrates how the optimal truck route time, distance, and air emissions are influenced by the compositional features of waste materials. The travel distance in each of these scenarios varies by up to 19.9% when compared to the composition that remains unchanged. In their study, Nowakowski et al. (2018) use a hybrid GA to maximize location attendance and waste collection while minimizing travel distance and vehicle usage.

Only a few previous researchers use ANN and LR techniques for vehicle routing related to waste collection. For example, Azadi and Karimi-Jashni (2016) predict the necessary frequency of collection at various locations using MLR and ANN models. The results show that a 10% decrease in collection frequency occurs when socioeconomic and demographic factors are included in the model. By avoiding serving areas with empty bins, the models reduce collection costs and their negative environmental effects.

4.2.5. Waste treatment and recycling

Predicting process parameters and predicting process output are the two MWM classifications in this study that deal with the use of AI techniques for the recycling and treatment of municipal waste (Birgen et al., 2021; Guo et al., 2021).

4.2.5.1. Predicting process parameters. MWM can be used to produce sustainable energy through waste conversion techniques like pyrolysis, gasification, and combustion (Andeobu et al., 2022b; Zhang et al., 2023a). The proper design and operation of waste-to-energy technologies require process variable modelling and optimization (Adamović et al., 2018). The application of AI to forecast high/low heating values and co-melting temperatures of solid waste has been the subject of a small number of studies for more than a decade (Alrayes et al., 2023; Ezzahra Yatim et al., 2022). Vyas et al. (2023) forecast the co-melting temperatures of fly ash and sewage sludge ash generated by an incinerator supplied with municipal waste using GA and ANNs. The study shows that GA and ANNs can still generate precise predictions in situations where there is insufficient data. Similarly, using single/double layer ANN models, Pandey et al. (2016) predict the low heating values and syngas yield in a fluidized bed reactor gasification process. The study suggests that double-layer ANN models need more computation time than single-layer ANN models. In a similar vein, Dashti et al. (2021) use GA and SVM to predict that solid waste would have a high heating value. Their analysis shows a high rate of prediction accuracy.

4.2.5.2. Predicting the process output. MWM optimization requires quantifying energy and biogas as well as potentially hazardous and beneficial byproducts like leachate and other emissions (Guo et al., 2021; Vyas et al., 2023). AI techniques have been developed by numerous research projects to predict the composition and quantity of different byproducts produced by MWM operations (see Table 2). Several ANN algorithms are compared by Behera et al. (2015) to forecast the amount of biogas that bioreactor landfills yield. Abu Qdais et al. (2010) investigate the use of ANNs and GA to optimize and simulate methane generation. After evaluation, the model shows a high degree of accuracy. Lawal et al. (2021) predict and optimize the energy generated from solid waste fractions using ANFIS, ANN, and MLR. Further, the study offers a method for selecting the most accurate predictive model. Established models are found to have satisfactory reliability based on a variety of prediction performance indicators. SVMs can also be used to categorize the results of waste processing, based on operational characteristics, for example, assessing the quality of recovered materials or the effectiveness of energy recovery in waste-to-energy plants (Zhu et al., 2019). Likewise, LR is frequently used as a straightforward yet powerful prediction tool for process optimization in scenarios where linear relationships between input factors (such as waste composition, processing time) and output variables (i.e. energy yield, material recovery rates) are present (Ho Park et al., 2021).

4.2.6. Planning for waste management

Making decisions and optimizing management practices are essential components of MWM planning to achieve particular strategic goals (Nowakowski et al., 2018). Huang and Koroteev (2021) state that MWM planning encompasses a wide range of activities, including cutting waste management costs, creating waste collection strategies, building MWM facilities, preventing the illegal dumping of solid waste, and considering the environmental effects of solid waste collection, transportation, treatment, and disposal. AI techniques are used in many studies to plan waste management strategies. SVMs and satellite data are utilized by Lanorte et al. (2017) to locate agricultural plastic waste, assist in the siting of solid waste facilities, and make route planning easier. With a 94.5% accuracy rate, SVM is effectively utilized to classify images and distinguish between plastic waste and crops. SVM is also successfully used to classify images and differentiate between crops and plastic waste, with an accuracy rate of 94.5% (Buenrostro-Delgado et al., 2015; Jacob and Banerjee, 2016) employ GA-based models for MWM planning. The higher parametric sensitivity of GA heuristics in comparison to the greedy randomized adaptive search procedure (GRASP) heuristics may affect the solution. Despite this, GRASP heuristics took roughly 29% longer to compute than GA. LR is used to examine how socioeconomic factors affect the rates at which waste is generated, providing information to support specific waste reduction efforts (Ezzahra Yatim et al., 2022). Urban planners can make data-driven decisions with the help of interpretable models made with DTs to identify those key factors influencing the performance of waste management (Meza et al., 2019).

4.3. Comparative analysis

The comparative analysis of different AI techniques - ANN, SVM, LR, GA, and DT - provides significant insights into their efficiency and performance in MWM. With its constant ability to handle intricate, nonlinear interactions, ANN is a very successful tool for a variety of applications, including the prediction, classification, and forecasting of waste characteristics and process output (Almomani, 2020; Cho et al., 2021). However, real-time or resource-constrained situations face difficulties due to their dependency on huge datasets and substantial processing resources (Yang et al., 2018). On the other hand, SVM excels in classification tasks, especially those involving high-dimensional data, such as bin-level monitoring or waste classification (Altin et al., 2023; Liu et al., 2020). Although it is resistant to overfitting, scaling problems in large datasets and the difficulty of parameter adjustment can make it difficult to apply (Zhang et al., 2023b). Besides, although GA has good optimization properties that make it useful for dynamic tasks such as waste collection and route planning, its applicability in real-time operations may be limited by its high computational cost and potential for local optima convergence (Pourreza Movahed et al., 2020). On the other hand, LR, despite its simplicity, offers a dependable starting point for linear relationships under stable circumstances, including forecasting the results of waste treatment or first evaluations in planning scenarios (Ho Park et al., 2021; Ezzahra Yatim et al., 2022). However, LR is incapable of simulating the non-linearities present in more intricate waste management procedures (Cho et al., 2021; Wilts et al., 2021). Besides, DT is quite useful in applications that need to be interpretable, including waste planning and classification, given its clear and simple framework for making decisions (Deepnarain et al., 2019; Xia et al., 2022). However, it is prone to overfitting, especially in noisy or highly variable datasets; this could impair its effectiveness in dynamic settings (Ding et al., 2023).

Hybrid models, such as ANN-SVM, take advantage of SVM's resilience in classification and ANN's ability to recognize patterns (Abdallah et al., 2020; Cha et al., 2022). These models are especially useful for difficult tasks where accuracy and generalization are crucial, including waste classification and bin-level monitoring (Ayeleru et al., 2021; Liang et al., 2021). Conversely, GA-ANN hybrid models combine the evolutionary search power of GA with the data-driven flexibility of ANN to perform exceptionally well in optimization tasks such as waste collecting and route planning (Abu Qdais et al., 2010). This combination improves the model's prediction ability as well as the optimization process. However, hybrid models have a trade-off in terms of their computational complexity and fine-tuning; this can lead to higher resource consumption and implementation difficulty (Liang et al., 2021). Despite these limitations, hybrid models are effective in meeting the complex requirements of MWM since they frequently perform better than single-method techniques in scenarios that call for a balance among categorization, efficiency, and predictive accuracy (Kuo et al., 2012; G. Liang et al., 2021).

5. Discussion

This research employs a SLR to examine how AI techniques can improve different aspects of MWM. The study's primary focus is on the application of AI techniques in MWM. It also compares the efficacy of these techniques, examines opportunities and challenges, and provides best practices for maximizing resource efficiencies to improve MWM system outcomes. The literature on AI techniques in MWM practices has been reviewed by considering secondary data from 2010 to 2024.

It is clear from the analysis in the previous sections that AI has risen to the top of the list of recent innovations that have the potential to be a game changer. AI is gaining traction across various sectors and is rapidly becoming a vital tool for governments, corporations, and other institutions to enhance financial performance and operational efficiency (Andeobu et al., 2022b). Many businesses now have the chance to sustain their prosperity and global competitiveness because of AI.

The present study focuses on five AI techniques that are frequently employed for modelling and optimizing MWM processes, although a variety of technologies are applied in the management and recycling of municipal waste. These AI techniques include ANN, DT, SVM, GA, and LR. The results of this study show that, when it comes to estimating waste production, AI-based techniques are more accurate than traditional ones. Predicting the characteristics of waste is the main focus of the majority of early research on AI applications in MWM. Waste generation and forecasting is the application area that has been most extensively researched in these studies. In those applications, ANN techniques are most frequently employed, followed by SVM, LR, and GA. While DT and SVM are only employed in a small number of studies, ANN, GA, and LR are the most often utilized techniques for bin-level monitoring, waste collection, vehicle routing and planning, waste sorting, and waste treatment and disposal.

The application of AI techniques in MWM is explored through the prediction of process parameters and output. Calculating beneficial byproducts, energy and biogas, as well as hazardous products, leachate and other pollutants, is essential (Azadi and Karimi-Jashni, 2016). Numerous studies document the use of AI techniques to predict the volume and composition of various byproducts from solid waste (Andeobu et al., 2022b). Recently, ANN has been used to optimize the conditions of the process for producing energy from landfill waste components. For example, temperature and pressure are optimized using an ANN model (Behera et al., 2015).

A recently published study offers great insight into the use of ANN, gradient-boosting trees (GBT), and random forest (RF) in the prediction of hydrothermal carbonization parameters. The composition of municipal sludge is examined to see if it improves its heating value, generates more energy, or recovers carbon (Zhu et al., 2023). Municipal sludge is determined in this study to be a viable option for producing energy. It is essential to investigate the application of AI techniques to mixed municipal waste. Before such AI techniques can be further expanded to consider alternative methods of treating municipal waste in conjunction with energy production, more research and analysis are required. This will lead to an improved system that will precisely direct MWM to address the amount of carbon emissions that can be reduced in the waste recycling industry in a manner that is both effective and sustainable. As a result, a suitable AI technique can be created to forecast energy production and can also be used as a legitimate and trustworthy instrument to identify the parameter values required for successful variable modelling.

Concerning this study, there are opportunities and challenges associated with adopting AI-based techniques. However, when used properly, AI techniques can be a source of business innovation. AI improves MWM processes, productivity, and efficiency while lowering operating costs and introducing new consistency, speed, and scalability levels (Ahmed et al., 2024; Bhattacharya et al., 2024). Further, AI-based techniques have the potential to help achieve Sustainable Development Goals (SDGs). For instance, in the circular economy, AI can help achieve SDG 12 (responsible consumption and production) and SDG 9 (industry, innovation, and infrastructure) (Andeobu et al., 2022b). AI can also be used to support and enhance ecosystem health to accomplish environmental goals that are in line with both SDG 7 (affordable and clean energy) and SDG 13 (climate action) (Naveenkumar et al., 2023; Zhang et al., 2023a).

Beyond aligning with the SDGs, the implementation of AI techniques can expedite the formulation of directives specific to waste management; these include (a) optimizing administrative body control; (b) increasing producer commitments through product responsibility programs; (c) conserving natural resources dramatically; (d) lowering risks to human health and the environment; and (e) simplifying the monitoring and management of solid waste (Chu et al., 2022; Liang et al., 2021). According to both Liang and Gu. (2021) as well as Lu et al. (2022), businesses and the waste management industry can put the right policies and procedures in place to help them better handle waste management systems thanks to AI techniques such as deep learning, machine learning, and natural language generation. Further, by lowering the cost of waste processing and developing environmentally friendly processing options, AI can assist in offering effective and efficient waste management solutions, paving the way for a society with little waste production (Andeobu et al., 2022b).

The content results analysis reveals further barriers/challenges in implementing appropriate AI techniques in MWM. Most papers reviewed for this study directly apply AI techniques to address particular MWM issues. Few studies use customized AI techniques to address the unique traits and attributes of MWM systems. Robust collaborative research amongst multidisciplinary teams of computer scientists and waste management experts is needed to design specific AI applications with the unique properties of MWM systems; a strong emphasis is needed to have highly qualified technical AI teams. Meanwhile, it is extremely difficult to create and apply AI technologies and applications in the field of MWM since reliable and secure applications depend on good engineering practices (Xia et al., 2022). Organizations across a range of industries, including MWM companies, have expressed

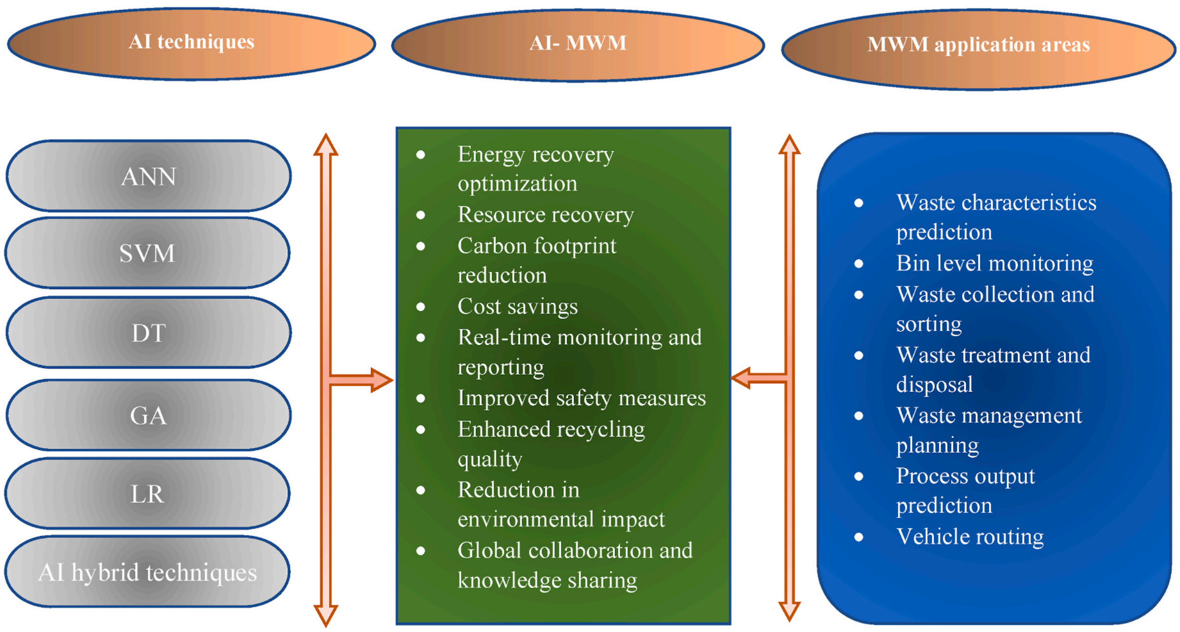

Fig. 7. Conceptual framework.

concerns about the increasing prevalence and universality of AI applications and technologies (Pitakaso et al., 2024; Seyyedi et al., 2024). Thus, applications and technologies utilizing AI that are more thorough, moral, open, equitable, and responsible are becoming more and more necessary.

AI-enabled creative MWM applications and systems can be used to mitigate the health risks associated with the collection, sorting, treatment, recycling, and disposal of municipal waste, as well as the time and energy expenditures involved. However, this study uncovers challenges that need to be addressed. Smart AI-based MWM is now necessary due to the mounting burden of population growth and landfill site exhaustion, as well as the requirement to be able to overcome the risks to the environment and public health posed by solid wastes (Ahmed et al., 2024). In addition to addressing the climate crisis and contributing to the creation of a more sustainable and healthier environment, adopting an AI-enabled innovative MWM system will help properly confront and resolve issues related to inappropriate municipal waste dumping. Furthermore, we present a novel conceptual framework that has been carefully developed, using knowledge from our extensive descriptive and content analysis of academic literature. This framework, as illustrated in Fig. 7, consists of three fundamental pillars that capture the role of AI in the sustainable management of municipal waste. These three pillars cover a variety of key elements, such as AI techniques, MWM application areas, and the resulting sustainability outcomes.

5.1. Future research perspectives

MWM will alter due to AI-powered smart recycling equipment. This will have a major positive impact on preserving the environment for a more optimistic and sustainable future (Birgen et al., 2021). The majority of AI techniques are still in the research and development (R&D) phase, despite the rapid advancement of MWM-related AI research. Understanding the opportunities and challenges inherent in these systems and applications is fundamental to developing dependable AI-based MWM applications and systems in the future. The commercialization of AI-based plans will aid the general objectives of environmental preservation and sustainable development. To ensure the full application of these methods, more research is required, focusing on the creation of reasonably priced AI-based techniques. Future critical and straightforward sorting, affordable and effective transportation, planned resource recovery, and efficient municipal waste disposal will all be ensured by the implementation of AI-based MWM. To improve general health conditions in low-income countries, it is critical to strategically develop low-cost AI-based MWM systems that can be installed there. AI-driven innovations will pave the way for better environmental monitoring and management. Table 3 presents a SWOT analysis of the AI techniques used in this study along with proposals for further research.

5.2. Implications

Our research provides practical implications for policymakers, municipal managers, and AI developers working in the field of MWM. To increase adoption and maximize impact, AI developers should prioritize aligning their models with real-world MWM needs and validating their solutions across a variety of datasets.[2] Our analysis identifies critical features that AI-based techniques should incorporate, including accurate waste bin level monitoring, reliable trash forecasting, and efficient vehicle routing. To facilitate interoperability among existing municipal systems, developers should provide user-friendly interfaces and ensure compliance with environmental and data regulations. As a result, policymakers and practitioners should adopt the proposed conceptual framework to address MWM challenges holistically, guiding the integration of AI into planning, operations, and long-term sustainability efforts.

Our research helps waste management stakeholders and municipal authorities understand that addressing internal and external enablers is necessary for the successful implementation of AI in municipal waste management (MWM). Stakeholders may need to prioritize developing internal strategies and/or external partnerships, depending on the particular MWM application area, such as waste characteristics forecasting, waste bin level monitoring, or process parameter prediction. Externally, collaborations with AI providers and interaction with regulatory agencies are necessary to promote the creation of customized technology solutions and provide guidelines that facilitate the

[2] https://www.weforum.org/stories/2021/04/how-ai-can-cut-waste-in-manufacturing/.

Table 3
SWOT analysis of the frequently adopted AI techniques in MWM and research opportunities.

AI techniques	Strengths	Weaknesses	Opportunities	Threats	Future research opportunities	References
ANN	• Capacity to model intricate and non-linear relationships • Fewer parameters are needed for calibration in multivariate systems than in deterministic models • Fewer parameters are needed for calibration in multivariate systems when compared to deterministic models • Fault tolerance	• Easily overfitted • Unable to establish correlations between the many variables at play • Inept at solving arithmetic and logical problems	• Source of business innovation, when properly applied • Used in practically every industry to improve productivity, security, and quality of production processes	• Privacy concerns: AI-powered businesses have encountered malicious attacks and privacy failures. • Inadequate design of AI systems can lead to safety concerns	• How could ANNs be used to maximize energy recovery, reduce emissions and lower operating costs in waste-to-energy facilities and anaerobic digestion plants? • In what ways can ANNs help in the creation of decision support systems that offer immediate insights into MWM operations, enabling municipalities to take preventative measures against problems such as illicit dumping or equipment malfunctions?	(Yang et al., 2018; Ezzahra Yatim et al., 2022; Chu et al., 2022; Seyyedi et al., 2024)
DT	• Minimal processing expenses • Results are simple to grasp • Capacity to handle missing values and pertinent features	• Overfitting of data and poor generalization of trained data sets	• Handle difficult issues in MWM, welfare, energy, safety, health, environment, infrastructure, transportation, and education.	• Privacy problems: AI-driven businesses have had malicious attacks and privacy failures • Inadequate design of AI systems can lead to safety concerns	• How can DTs be integrated into MWM decision support systems to give real-time feedback and recommendations for maximizing operational effectiveness and reducing environmental impact? • How can DTs be used to help MWM systems in risk assessment and contingency planning?	(Guo et al., 2021; Vyas et al., 2023; Hoy et al., 2024b)
SVM	• Minimal mistakes in generalization • Minimal computational expense • Reduction in the vulnerability to overfitting	• Extremely sensitive to certain turning variables and kernel selection	• Robust business support that fosters competitive advantage and enables businesses to adjust quickly	• Privacy problems: AI-driven businesses have encountered malicious attacks and privacy mistakes. • Inadequate design of AI systems can lead to safety concerns	• What strategies can combine SVMs with public engagement and education programs such as creating outreach campaigns and targeted messaging to encourage recycling, waste minimization, and appropriate disposal practices? • How can SVMs be used to maximize efficiency and quality of outputs by analyzing process variables, equipment performance, and material flows in waste treatment facilities such as composting plants or material recovery facilities?	(Dai et al., 2011; Vu et al., 2019; Andeobu et al., 2022b)
GA	• Simple programmability • High precision	• Demands meticulous design • Results could be negatively impacted by an operator's incorrect choice	• Can play a major role in enabling strategic priorities • Utilized to increase the profitability and efficiency of businesses	• Privacy problems: AI-driven businesses have encountered malicious attacks and privacy failures • Inadequate design of AI systems can lead to safety concerns	• How can GAs help MWM with long-term strategic planning that takes into account variables such as urbanization, population growth, and technology improvements to foresee opportunities and challenges in the future? • How can social, ethical, and legal issues surrounding the incorporation of GAs into MWM systems be resolved to guarantee openness, equity, and public acceptance?	(Jacob and Banerjee, 2016; Ibrahim et al., 2024; Bhattacharya et al., 2024)
LR	• Minimal computational expenses • Simple results interpretation	• Unsuitable for modelling non-linear data	• Assists companies in thriving in a world where business disruption is constant • Can play a major role in enabling strategic priorities.	• Privacy-related concerns	• How can geographic information systems (GIS) and LR be combined to map waste generation patterns geographically, locate high-waste-generation areas, and potentially identify service-density disparities? • How can LR be applied to support sustainable decision-making by quantifying the environmental effects of	(Liang and Gu, 2021; Ezzahra Yatim et al., 2022; Chu et al., 2022)

(continued on next page)

Table 3 (*continued*)

AI techniques	Strengths	Weaknesses	Opportunities	Threats	Future research opportunities	References
					various waste management techniques, such as carbon emissions, energy consumption, and resource depletion?	

incorporation of AI into waste management systems.[3] Internally, our findings emphasize the significance of organizational readiness, which includes having a clear plan for using AI-based techniques, encouraging innovation, identifying processes that can be automated, and making sure that IT infrastructure is reliable. New fields, including trash bin level monitoring, may place more emphasis on outside cooperation to improve AI technology and guarantee interoperability with current waste management systems. Achieving long-term sustainability in MWM processes and enabling smooth AI integration require strategic change management, process adaption, workforce training, and IT support.

Our analysis emphasizes how urgently governments and regulatory agencies must assist in accelerating the use of AI in MWM. We stress the significance of making investments in digital infrastructure at policy level to facilitate smooth AI integration, especially in developing countries where resource limitations may impede technical developments. AI-driven efficiencies can help emerging as well as developed countries tackle issues such as increasing urban trash volumes and a shortage of workers. Our findings also recommend government efforts to co-finance crucial research, including extensive pilot studies, to verify AI models in actual MWM settings and guarantee responsibility for AI-driven decisions. We also emphasize the necessity of defined rules for data collection and sharing to give AI developers efficient and moral access to high-quality datasets for testing and training models. Finally, we advocate public awareness campaigns and stakeholder engagement initiatives to foster acceptance of AI- based techniques among waste management professionals as well as communities, thereby ensuring sustainable development of waste management systems and broader societal benefits.

6. Conclusion

The primary goal of this study is to document the state of practice and research at present, as well as any potential applications of AI techniques for MWM system optimization. 229 pertinent articles published at the intersection of MWM and AI between 2010 and 2024 are chosen and examined using a systematic literature review. In an attempt to optimize the performance of MWM systems, this study looks at the application of AI techniques in several MWM-related areas, including generation, sorting, collection, vehicle routing, treatment, disposal, and waste management planning. This research conducts a SWOT analysis and comparison of the five AI apps that are commonly used in MWM. The results show that the AI-based techniques (ANN, SVM, DT, GA, and LR) have good forecasting and prediction performance in the various MWM features covered in this study for optimizing MWM practices. Besides, the bulk of MWM problems are intrinsically complicated, ambiguous, and poorly defined, since waste management has historically been a manual procedure. Therefore, in many MWM scenarios, especially those affected by a lack of data, the traditional MWM practices - which are based on inflexible algorithms and mechanistic models - do not seem to offer a satisfactory solution. In the MWM sector, there is a lot of interest in AI-based techniques as possible alternatives. The research findings have several significant implications for future research into AI-driven MWM systems. Even while the application of AI techniques - ANN, SVM, DT, GA, and LR - has shown good prediction and optimization skills in a variety of waste management processes, there are still a few gaps that need to be filled. Firstly, the study emphasizes the necessity for a more thorough investigation into the use of AI in unexplored areas including waste management, biogas generation, and waste-to-energy operations. Although they need deeper examination, these areas hold great promise for improving MWM processes. Further research could focus on how AI could accelerate these processes to mitigate their negative effects on the environment and enhance resource recovery. Furthermore, more research is needed to determine how AI-driven MWM systems may affect the environment, particularly concerning emissions from treatment and transportation processes. For instance, research could look into how AI techniques can be used to anticipate and reduce the environmental impact of waste management operations, in line with sustainable development goals.

Further study is required to address the issues of data scarcity and quality; these remain as barriers in preventing the broad adoption of AI in MWM. While large datasets are necessary for training and validation in many modern AI applications, MWM systems frequently function in settings with insufficient or missing data. Future research might concentrate on developing AI techniques that are more resistant to data constraints, including hybrid models that include many AI techniques for more precise predictions in situations with sparse data or transfer learning. This study also identifies important gaps in the social and ethical aspects of AI applications in MWM. While there are clear advantages to AI-driven developments, issues with data privacy, cybersecurity, and equitable distribution of AI-enabled technology need to be addressed. Future studies could focus on developing guidelines for the ethical and transparent application of AI in MWM, making sure that these tools help all stakeholders involved. Finally, future research should focus on integrating cutting-edge AI techniques, especially deep learning, generative artificial intelligence, and metaheuristics. Although these techniques have shown potential in other fields, they are still not widely used in MWM. As such, new levels of efficiency and adaptability, particularly in complex metropolitan areas, could be unlocked by examining the scalability and resilience of these techniques in the context of real-world MWM systems.

This study has certain limitations, but they may open doors for further investigation. Firstly, the review examines only articles and reviews, resulting in fewer papers being examined. Therefore, researchers may consider more diverse papers in the future. Secondly, mapping all the dimensions of AI in MWM requires more than one qualitative review. Thirdly, this research is limited by the assumption of reality in the data and analyses from earlier investigations. While subjectivity is involved, unavoidably, in some of the analyses in this study, it serves as a foundation for future investigations into integrating AI techniques in diverse MWM areas. Furthermore, other cutting-edge technologies are available to create and improve MWM systems besides AI. Thus, to attain the sustainable development of MWM systems, additional technologies such as blockchain, IoT, digital twins, etc. may be subjects for future research.

CRediT authorship contribution statement

Asmae El jaouhari: Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Ashutosh Samadhiya:** Writing – original draft, Supervision, Methodology, Funding acquisition, Data

[3] https://www.marketsandmarkets.com/Market-Reports/waste-management-market-72285482.html.

curation, Conceptualization. **Anil Kumar:** Writing – review & editing, Resources, Project administration, Formal analysis, Conceptualization. **Eyob Mulat-weldemeskel:** Writing – review & editing, Supervision, Project administration, Investigation. **Sunil Luthra:** Writing – review & editing, Supervision, Resources, Project administration. **Rajesh Kumar:** Supervision, Software, Methodology, Formal analysis.

Declaration of competing interest

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

Data availability

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

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