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Model structures and approaches for municipal solid waste prediction – A review

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ABSTRACT

Understanding the generation patterns of municipal solid waste and adapting to it is one of the most urgent problems of the decade, which requires meaningful answers in order to establish sustainable and resilient waste management infrastructures. The purpose of this literature review is to systematize the models and approaches that are suitable for predicting the amount of municipal solid waste (MSW). Based on systematically explored literature analysis (used Scopus database in 2023) methodologies, a recommendation framework is developed to underpin the design of municipal solid waste management systems by recording possible models and proxy variables in addition to presenting their advantages and limitations based on the 78 papers that met the selection criteria. The proposed framework identifies possible model structures according to the municipal solid waste management analysis task and data availability, which fills the gap and lays the foundations for data-based decision support in goal-oriented municipal solid waste management. A total of 36 AI-driven models are explored and catalogued using 455 proxy variables. Depending on the number of observations and the set of available proxy variables, a model structure framework is provided, based on which the identification of models can be optimized for the completion of goal-oriented municipal solid waste predicting tasks. This literature review provides a basis for meeting the goal-oriented MSW modeling tasks at a higher level, as it also proposes a model catalog, data inventory and model structures, and discusses how to address the challenges that may arise for the models. It is the first research to distinguish modeling issues of interest to industry professionals and academics, thereby providing guiding results for the entire municipal solid waste management sector.

1. Introduction

The growing municipal solid waste is a complex problem that affects all citizens worldwide (Maalouf and Mavropoulos, 2023), regardless of their location or lifestyle. According to the World Bank's estimate, the amount of waste is projected to increase from 2.01 billion tons in 2016 to 3.40 billion tons by 2050 (Kaza et al., 2018). This increase can cause numerous problems of which environmental pollution is the most significant (Mor and Ravindra, 2023). Landfilling and incineration of municipal solid waste can release harmful substances into the environment (Cai et al., 2023), including toxic compounds (Kolawole et al., 2023), greenhouse gases (Pamukçu et al., 2023), and other pollutants (Kaur et al., 2023).

Changes in waste quantity and composition can significantly impact the appropriateness and effectiveness of waste management technologies, therefore accurate prediction and efficient management of municipal solid waste (MSW) volume is essential in safeguarding the environment, fostering economic growth, and protecting human health (Kumar et al., 2020). Predictions can assist waste management providers and authorities in planning waste collection and management strategies. This allows for effective responses to expected changes in waste volumes, leading to better planning and optimizing processes and operational costs (Zhao and Li, 2023). As a result, more cost-effective waste collection, transport, and treatment methods can be developed and applied, and available resources can be used more efficiently (Dyson and Chang, 2005). On the other hand, to ensure efficient and sustainable waste management it is crucial to consider demographic changes, economic development, lifestyle changes, and other external factors that may impact the amount of municipal solid waste produced (Sun and Chungpaibulpatana, 2017).

Additionally, predictions can serve as a tool to increase education and social awareness. The data can help us understand the environmental and economic impacts of waste generation and encourage individuals to reduce waste and recycle. This allows the modeling tasks to be grouped in a goal-oriented manner, which is presented in detail in Fig. 1, indicating the data sources and modeling context. Currently, there is no scientific publication that covers the methods, data sources

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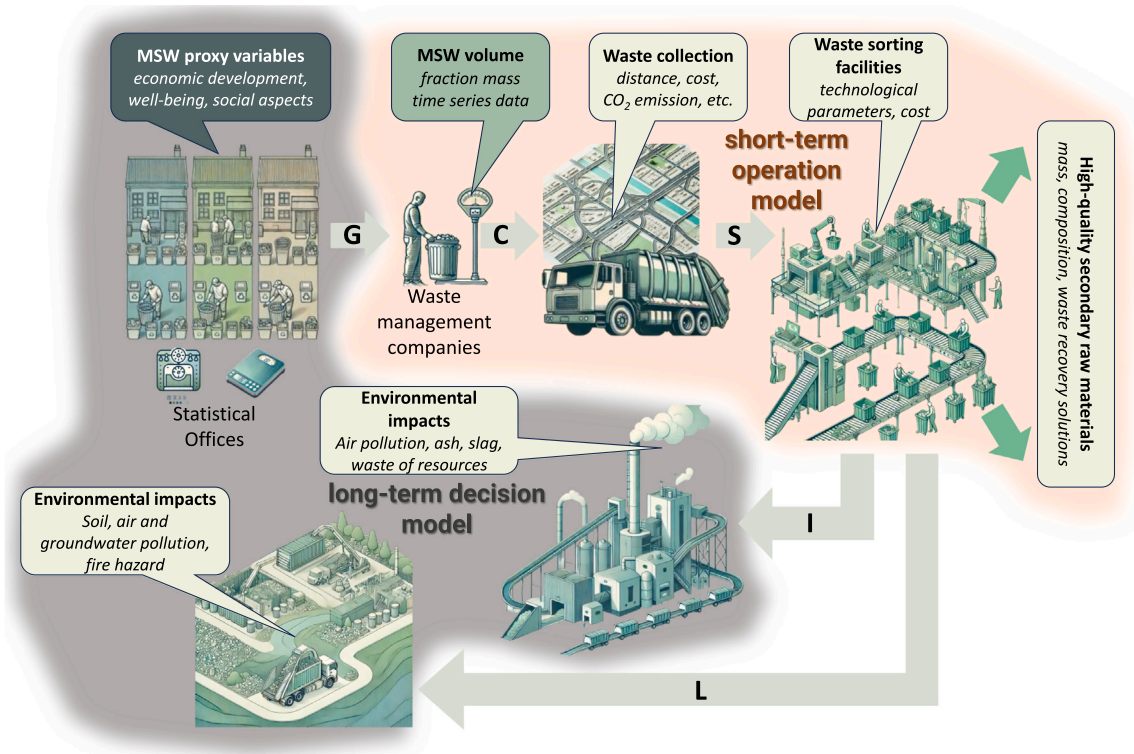

Fig. 1. Waste management analysis tasks, data sources and consequences: GCSIL model framework (G: generation, C: collection, S: sorting, I: incineration, L: landfilling)

and model building related to MSW quantity modeling in their entirety, therefore the primary goal of this review is to attempt to fill this gap.

In Fig. 1, the GCSIL (G: generation, C: collection, S: sorting, I: incineration, L: landfilling) model was introduced, which integrates the waste management sector-specific analysis tasks, data sources and consequences in a unified framework. This is important because different types of modeling tasks (strategic decision models and operational models) require specific model structures. Without this kind of separation, decision support cannot be implemented at the expected level.

In the review article, the examination of waste predicting tools according to the framework presented in Fig. 1. This framework enables a classification of models into two main groups according to the municipal solid waste management analysis tasks: on the one hand the planning and selection of elements of a long-term waste management strategy, and on the other hand, the development and planning of everyday operation technology. For the technological issues, high-quality and frequent data is provided by specific long-term time series data (Fig. 1 gray box), which can be obtained mainly from waste management companies. For the strategy planning, less frequent data is provided by a wide range of proxy variables (Fig. 1 green box) that can be used to describe with a high degree of accuracy the environment that influences waste generation.

The diversity of predictive models and the availability of data can result in a challenging decision-making process for individuals. This problem is illustrated in Fig. 1, which shows two decision processes and their associated waste management consequences. The application of the framework in this research would guide the most efficacious approach, including waste management task orientation, the mechanisms and requirements of different models, including data dimensions, granularity, and quantity. The primary aim of this literature review is to serve as a guide for readers to select the most appropriate model structure based on their requirements and possibilities, for which the decision tree-based model structure selection logic is developed.

1.1. AI in municipal solid waste management

Artificial intelligence (AI) tools were successfully applied MSW (Abbasi and El Hanandeh, 2016) and biomass (Yatim et al., 2022) characteristics, odor emission (Xu et al., 2022), plastic waste sorting efficiency improvement (Nguyen et al., 2024), illegally dumped waste detection (Majchrowska et al., 2022), biomedical waste reduction (Sengeni et al., 2023), reduce food waste (Maiyar et al., 2023), decision support system in civil engineering (Santos et al., 2024), sorting by a robot with AI (Wilts et al., 2021), waste bin level detection (Abdallah et al., 2020), process parameters prediction (Stergiou et al., 2023), vehicle routing (Revanna and Al-Nakash, 2023), wastewater treatment plans parameter prediction (Aghdam et al., 2023). Nevertheless, the most common application of AI in the field of waste management is the description of the operating system and the implementation of predicting tasks, therefore we are examining the applicability of AI tools to perform these tasks to improve the reliable operation and support the strategy planning of the future challenges of the municipal solid waste treatment.

1.2. Data sources of waste prediction

According to the framework presented in Fig. 1, two main groups of data sources can be used for waste management analysis tasks. For strategic analysis, to integrate proxy variables, international databases have been developed to facilitate the tracking of waste generation, economical and social variables. Eurostat offers 4243 data sources broken down by statistical topic, the time coverage of which varies depending on the data (Eurostat, 2025). The data is available for the countries of the European Union. Waste generation data is included, therefore it is suitable for supervised learning tasks. Another useful data source is the OECD database, where 288 indicators are available in annual breakdown (OECD, 2025). Both data sources can be dynamically queried via Application Programming Interface (API), further supporting their applicability. In Appendix C of "What a waste A Global Review of Solid Waste Management" we can find further valuable resources for modeling different countries (Hoornweg and Bhada-Tata, 2012). The United Nations Environment Programme (UNEP) (Wilson et al., 2015) also produces reports analyzing sustainable management methods, and the Basel Convention contains data on hazardous waste. The UN Sustainable Development Goals (SDGs) (Assembly, 2015) are closely linked to waste management, with the overarching ambition of the SDGs being to end poverty, protect the planet and ensure prosperity for all (United Nations Department of Economic and Social Affairs, 2025), which contains 706 data series for all countries and regions. As a global data source, the World Bank database contains useful proxy variables in 86 databases. The exploration of UN & World Bank global data sources can also be supported with APIs. Specific data sources from waste management companies can be used to model technological development tasks. Detailed time series data per waste fraction, per collection vehicle (Fig. 1 for green beans), and technological parameters can be integrated into waste management analysis tasks.

1.3. Granularity and quantity of data

The selection of predicting methods employed is contingent upon the quantity and quality of the available data. In instances where the amount of data is limited, rudimentary statistical methods such as averaging or linear trend analysis (Wikurendra et al. (2023); Khanal (2023)) can be utilized, though their precision may be constrained. An alternative approach involves analogy-based estimation (Meyer et al., 2020), where waste generation data from regions exhibiting analogous demographic and economic characteristics is employed to formulate predictions. Additionally, qualitative predictions can be constructed based on the expertise and knowledge of local specialists. For example, in the field of nuclear waste management, the United States Nuclear Regulatory Commission (NRC) has used this method in the performance assessment of high-level radioactive waste storage, where the integration of expert opinions was key to making long-term safety predictions (Bonano et al., 1990).

When a medium amount of data is available, more advanced methods can be employed. In cases where a characteristic is measured over a long period of time, such as the amount of waste in a bin or the number of times it is opened (Likotiko et al., 2020), time series analysis, such as the ARIMA (Auto Regressive Integrated Moving Average) model, can be utilized. This takes into account the time dependencies and trends of the data, thus providing more accurate predictions. In instances where the time horizon is brief but there are multiple variables available for modeling, regression models (Estay-Ossandon and Mena-Nieto, 2018) can be utilized to examine the relationship between, for instance, waste volume and one or more independent variables, such as population or economic indicators.

In the context of large data sets, the most sophisticated techniques can be employed. Multivariate regression (Cubillos, 2020), for instance, incorporates numerous variables, including economic indicators, population growth, and consumption patterns, thereby facilitating a comprehensive analysis of the factors influencing waste production. The application of artificial intelligence and machine learning methods, such as neural networks or decision trees (Kannangara et al., 2018), enables the identification of intricate patterns and the formulation of precise predictions. Temporal and spatial modeling (Johnson et al., 2017) employs geostatistical methods to analyze the spatial distribution and temporal changes of waste production, thereby providing more accurate regional predictions. As the amount of data increases, increasingly complex predicting methods can be utilized. While understanding and model description are facilitated by simple models, the ANN model becomes intractable when describing using equations and functions. Instead, learning algorithms or, for example, the number of layers and neurons are typically employed to characterize the model. Consequently, it can be posited that the comprehension of such models is directly proportional to the complexity of the methodologies employed. With the augmentation in both the quantity and the quality of the data, it becomes feasible to implement progressively sophisticated and precise prediction methodologies, which in turn can provide more effective support to decision-making processes in waste management and the formulation of long-term strategies.

A dataset is typically divided into three subsets: training, validation, and test (Golbraikh et al., 2003). The training subset is used to train the model, the validation subset is used to fine-tune the hyperparameters and evaluate the model during training, and the test subset is used to evaluate the model's generalization.

The effectiveness of machine learning models is determined by the data used to train them (Mahesh, 2020). Data interpretation, coding (Maiya, 2022), cleaning (Gudivada et al., 2017), and the creation of high-performance models (Wang et al., 2023) are all important steps in the machine learning process. An ideal dataset should possess certain characteristics. It must be of high quality as the accuracy of the model is heavily reliant on the quality of the input data. Noisy (Karimi et al., 2020), incomplete, or inaccurate data (Hao et al., 2020) can lead to weaker models. Additionally, it should be a sufficiently large amount of observations as the model requires enough data to learn the inherited connections in the data. In the case of small datasets, the model will become overtrained (Mohammadiun et al., 2022), resulting in good performance on the training dataset but poor performance on new data. Additionally, the model must be trained on a diverse dataset (Mandal et al., 2021) to ensure generalization to unseen data. However, an ideal data set is never available. Incomplete data sets are more likely to be available than complete data sets. Ignoring missing data leads to an inadequate model and thus to a failed prediction (Emmanuel et al., 2021). To replace these, there are several processes, such as deletion or input solutions. Regarding the amount of data, it is caused by the availability of a small amount of data (Xu et al., 2023). This can be solved in two ways. One is from the data point of view, increasing the data size in the process of data collection, for example, automatically extracting data from publications using NLP (natural language processing) (Jang et al., 2021) and TM (translation memory) technology (Sin-Wai, 2023). The other is from the point of view of machine learning, choosing a modeling algorithm suitable for small data sets, or improving model predictive accuracy through machine learning strategies, algorithms suitable for modeling with small data include support vector machine (Abdullah and Abdulazeez, 2021), random forest (Dou et al., 2023), gradient boosted decision tree (Brophy et al., 2023), and so on. The conclusion from the above is that there is no universally accepted solution, but the optimal model must be selected based on the available information.

1.4. Comparative exploration of the research gap

The aim of this literature review is to explore the models that have been used to predict MSW quantity in a structured way. We aim to create a database that can be used to select models and characteristics for a given waste prediction task "ex-ante". Our results will help to support the identification of MSW predicting models and shed light on areas where models should focus in the future. Various modeling aspects of municipal solid waste have been previously investigated, which is presented in Table 1.

Compared to previous studies, this study offers a more comprehensive and systematic approach to municipal solid waste predicting. While previous works, such as Alzamora et al. (2022) and Izquierdo-Horna et al. (2022), focused primarily on socio-demographic effects and influencing variables using traditional statistical methods or basic categorization, our study integrates a significantly broader methodological range. We analyzed 36 AI-based models and used 455 proxy variables, which allows for a much deeper and more detailed exploration of predicting opportunities. In contrast to studies that attributed a limited or moderate role to AI (e.g. Šomplák et al. (2023)), our study positions

Table 1
Comparison of scientific articles on waste management predicting.

Attribute	Focus	Methodology	Role of AI and ML	Applicability
Alzamora et al. (2022)	Impact of socio-demographic and economic factors on MSW	Linear regression and statistical analyses	Not significant	Planning socio-demographic analyses
Izquierdo-Horna et al. (2022)	Holistic approach, analysis of influencing variables	Categorization based on influencing variables	Moderate role	Supporting policy decision-making
Šomplák et al. (2023)	General modeling strategies	Time series models, scenario-based analyses	Less important	Scenario modeling
Xia et al. (2022)	AI and ML applications in the entire MSW process	AI-based algorithms and data-driven models	Very significant	Waste management optimization
Current paper	AI-based models and framework for MSW prediction	64 AI models and 455 proxy variables	Very significant	Model selection framework

AI and machine learning as central to the prediction accuracy and adaptability of the models. This emphasis on data-driven decision-making is consistent with the AI-focused framework presented by Xia et al. (2022), but goes beyond it, as our work goes beyond application to develop a generalized model selection framework. The novelty of this study lies in its comprehensive methodological synthesis, its significant integration of AI and ML, and its practical utility in supporting optimal model selection for various waste management scenarios, such as strategy creation and technology development. A comprehensive, data-driven modeling toolkit grouped by waste management analysis tasks has not been prepared, for which the authors aim to fill this urgent gap for the development of waste management value chain (technology) planning and waste strategy-making processes.

Municipal solid waste prediction is crucial for developing an efficient and sustainable waste management strategy. It should be widely used at all levels of waste management, from planning to implementation and evaluation. The purpose of this paper is to provide a scientific summary of robust communal predicting techniques, based on which a framework is presented to identify the optimal model structure for the prediction and decision-making support for strategy formulation.

1.5. Research questions and objectives

The following research questions (R_Q) and objectives (R_O) can be formulated regarding the quantitative prediction of municipal solid waste:

- R_{Q1}: How are AI-based and statistical models currently applied to municipal solid waste (MSW) quantity prediction?
  R_{O1}: Collection and analysis of methods used for quantitative prediction of municipal solid waste and provide a guide for optimal model structure identification.
- R_{Q2}: What data can be used for different modeling tasks?
  R_{O2}: To compile a specific set of variables that can be directly used in future studies.
- R_{Q3}:What are the differences in modeling applications related to technological developments (operational parameters) and political strategic decisions?
  R_{O3}: To provide a proposal for expert support for task-oriented model development at the model structure and state variable (data source) level.
- R_{Q4}:Depending on the available data and the analysis goal, which model is most appropriate to use?
  R_{O4}:Develop a specific recommendation system based on the data set and the analysis question.

2. Methods

The fundamental aim of this review is to support the performance of municipal solid waste (MSW) predicting tasks by collecting and processing in a structured manner the methods used in the international scientific literature. For which a model collection is developed that describes the model structures and the state variables (data) used. Our proposed methodology for the selection of the ideal model structure integrates the experiences of previous scientific applications into a unified framework (Fig. 2), based on which waste predicting and the necessary technology modifications can be implemented at a higher level.

Table 2
Inclusion logic for the identified papers.

Papers included	Papers excluded
MSW quantity prediction	MSW quality prediction
Model structure is described	No model structure
Used data is clearly presented	Treatment technology performance analyzed
Published in English	Published not in English
Full text available	Full text not available

A systematic literature review was conducted to explore the municipal solid waste predicting models. Predefined selection criteria were used to find empirical evidence to answer which model structures are the most accurate for MSW volume prediction. In this paper, the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) (Moher et al., 2015) framework is utilized, for which the following selection criteria were defined (Table 2):

As shown in Table 2, the prior aim of this review is to assist modeling tasks in identifying usable data and model structures, therefore only papers that contain the necessary details were selected. Searches were conducted in the Scopus database, covering articles indexed up to December 15, 2023 by the following string in Scopus:

"TITLE-ABS-KEY (municipal AND solid AND waste AND model AND forecasting) AND PUBYEAR > 2002 AND PUBYEAR < 2024".

After removing duplicates and studies that did not meet the above-mentioned criteria, the initial database search yielded 51 articles. Furthermore, 30 external articles were included based on the expertise of the authors. This process of article selection during the systematic review is illustrated in Fig. 2. All articles underwent manual screening and categorization based on their objectives, primary methods, geographic location, level of analysis, results, conclusions, and limitations, whose summary table is included in Appendix A. The information required for the analysis of the model structures was compiled into a single database, which includes the following categories: method, variables, time interval, frequency of data, number of observations, geographical location, and the length of the prediction interval.

In our proposed framework, a multi-step process supporting experts was defined to select the most suitable model for the predicting task. Firstly, it is necessary to check the number of available observations. If it is sufficient for the model to be identified, the next step is to check the set of available proxy variables. This step should be carried out in the same way as the previous one. If the number of variables exceeds those belonging to the given method in the database, it is recommended to identify the model using the available data. As a final step, it is advisable to perform cross-validation on a subset of the observations and conduct a statistical analysis of the data for the accuracy of the model to provide the highest possible value.

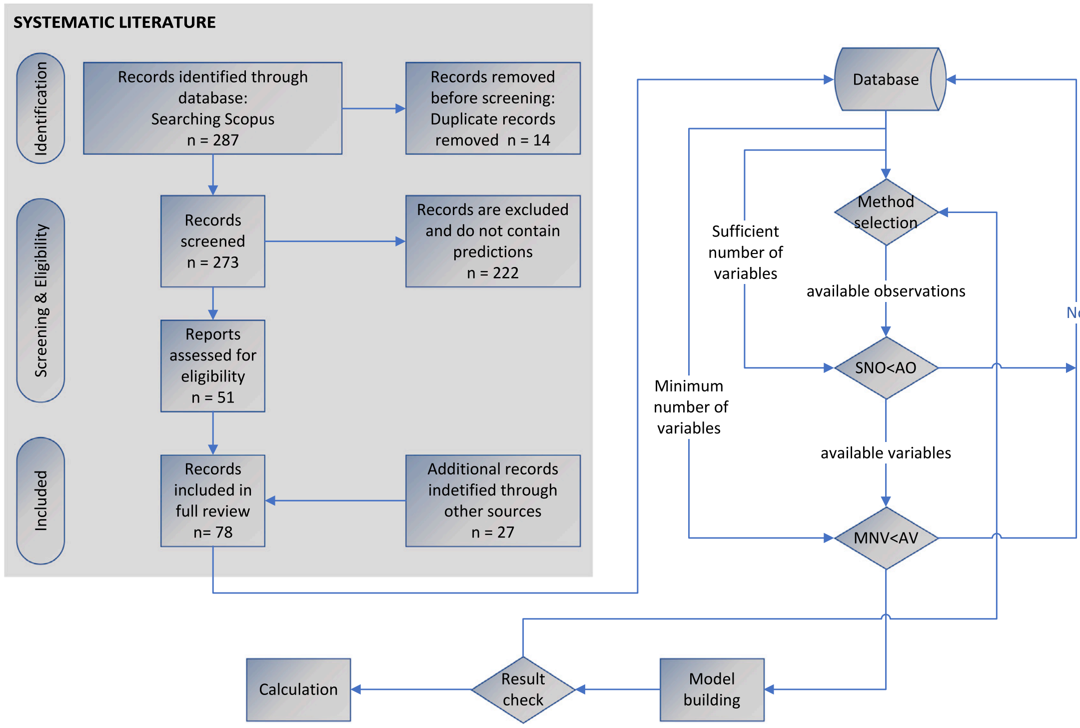

Fig. 2. Workflow of the proposed recommendation framework for optimal MSW prediction model structure.

Based on Fig. 2, it can be seen that depending on the number of data points and the availability of proxy variables, two-step feedback has been integrated into our proposed model structure selection framework. These feedbacks support the analyst in choosing the method that best fits the data from the 64 models and 455 variables explored in this research, which entails optimizing the accuracy of the model. Artificial intelligence-based models are the most common for predicting tasks (Wei et al., 2019), therefore the approaches most often used in the MSW literature are briefly presented, and their advantages and disadvantages are also highlighted in Table 3.

The advantages and disadvantages of the presented modeling approaches are shown in Table 3.

Depending on whether we want to identify the non-linear, robust, interpretable, multivariate, reduced model variance, seasonal or rank characteristics of the model, different model structures could be recommended (Table 3). Nevertheless, feature correlation, overfitting, missing data, outliers, etc. are problems that need to be taken into account in the initial phase of model identification.

It is imperative to emphasize the significance of high-quality, well-structured data when constructing machine learning models (Verdonck et al., 2024). The process of feature engineering, which involves the intelligent transformation of data or the creation of new, meaningful features, has been shown to have a significant impact on the performance of a range of models, from simple ones such as decision trees and regressions to more complex techniques such as neural networks and XGBoost (Ngo et al., 2024). In a similar manner, the process of feature selection, which involves the meticulous identification of salient features, has been demonstrated to enhance the efficiency of models by decreasing computational demands and optimizing the utilization of resources, a benefit that is particularly evident in the context of substantial data sets (Binder et al. (2020); Tan et al. (2024)). In scenarios where data is sparse or noisy, the effective use of data handling techniques is paramount for the efficient extraction of useful information (Aigner and Körner (2020); Kovačević et al. (2025)). The combined use of hyperparameter optimization and feature selection has been demonstrated to enhance not only the predictive accuracy of machine learning models, but also their interpretability and cost-effectiveness (Enemosah, 2025).

3. Results

A total of 140 predictive applications were identified across the 78 studies included in the systematic literature review, which can be traced back to 36 distinct methods. The classification and relative frequency of the different methods are presented in detail in Fig. 3. The classification of predictive methods was based on the work of Yang et al. (2019), which mainly follows the classical grouping of artificial intelligence tools.

The purpose of Fig. 3 is to support the selection of possible model types and specific methods for MSW quantity forecasting tasks. Most models belong to the machine learning (ML) family, which accounts for about 73% of the total applications. Within this group, supervised (39 pcs.) and unsupervised learning (6 pcs.) tools, deep learning (46 pcs.), and ensemble methods (11 pcs.) can be distinguished. In addition, time-series forecasting (21 pcs.) (Khajevand and Tehrani, 2019), systems models (7 pcs.) (Eslami et al., 2021), statistical modeling (8 pcs.) (Zhang, 2013) and probabilistic models (2 pcs.) were also applied in the published papers. Dimensionality reduction (Noori et al., 2009b) and clustering solutions were used in unsupervised learning, while in supervised learning, regression techniques (20 pcs.) and clustering algorithms were most commonly used. Time-series forecasting accounts for 15.7% of all applications. This includes error, trend, and seasonality models with external variables (ETSX) (Fokker et al., 2023), Kuznets curve model, or Tapio elastic approaches (Wang et al., 2021). System dynamics models account for 4.3%, including, for example, the Kalman filter (Song et al., 2015). Neural networks and deep learning account for 32.9%, within which artificial neural networks (ANN) (Kulisz and Kujawska, 2020) are the most frequently used method (27 pcs.) for MSW quantity prediction among all methods.

Municipal solid waste volume forecasting tasks can be performed using different data sources depending on whether the goal is to create an operational or decision model. For the methods included in this literature review, the frequency of state variables used is shown in Fig. 4.

Fig. 4 includes the methods that were applied more than once to MSW prediction (22 of 36 methods) and the frequency of the

Table 3
Advantages and disadvantages of the most commonly used waste predicting methods.

Method	Application	Key variables	Advantages	Disadvantages
Linear regression	Khanal (2023)	Mixed	Simplicity and interpretability (Schielzeth, 2010)	Overfitting (Zanotti et al., 2019)
	Estay-Ossandon and Mena-Nieto (2018)	Mixed	Versatility (Rohlfs, 2023)	Problem of outliers (Çankaya and Abacı, 2015)
Decision tree	Kannangara et al. (2018)	Mixed	High interpretability (Shimizu and Kaneko, 2021)	Prone to overfitting (Khoshgoftaar and Allen, 2001)
	Zhao and Li (2023)	Mixed	High efficiency (Jin and Agrawal, 2003)	Ignore feature correlation (Hall, 2000)
Random forest	Singh and Uppaluri (2023)	Mixed	Reduce model variance (Genuer, 2012)	Not applicable to attribute data with different values (Xia et al., 2022)
Support Vector Machine	Ayeleru et al. (2021)	Mixed	Suitable for small sample problems (Liu et al., 2012)	Sensitive to missing data (Razzaghi et al., 2016)
	Meza et al. (2019)	Mixed	Avoid local minimums (Suykens and Vandewalle, 2000)	Sensitive to kernel selection (Ben-Hur et al., 2008)
Gradient Boost Regression tree	Lu et al. (2022)	Mixed	Rank feature importance (Pan et al., 2009)	Difficult to train in parallel (Wen et al., 2019)
ANN	Kulisz and Kujawska (2020)	Mixed	Suitable for any nonlinear relationship (Yu et al., 2006)	Need a lot of parameters (Almassri et al., 2018)
	Abbasi and El Hanandeh (2016)	MSW only	High robustness and fault tolerance (Dao et al., 2020)	Lack of interpretability (Fan et al., 2021)
ANFIS	Adeleke et al. (2022)	Mixed	Combine the advantages of neural network and fuzzy reasoning (Al-Mahasneh et al., 2016)	Not suitable for higher dimensional features (Seifi and Riahi-Madvar, 2019)
ARIMA	Marandi and Ghomi (2016)	MSW only	Simplicity and interpretability (Ilic et al., 2021)	Sensitivity to model assumptions (Wan Ahmad and Ahmad, 2013)
	Rimaitytė et al. (2012)	Mixed	Effectiveness for stationary data (Mondal et al., 2014)	Inability to capture nonlinear relationships (Khashei and Bijari, 2011)
SARIMA	Navarro-Esbrı et al. (2002)	MSW only	Handling seasonal patterns (Adams and Bamanga, 2020)	Requires more parameters to estimate (Dubey et al., 2021)
	Merelles et al. (2019)	MSW only	Improved predicting accuracy (Lee et al., 2018)	Assumption of linear relationships (Fang and Lahdelma, 2016)
LSTM	Srivastava and Jha (2023)	Mixed	Effective for sequence data (Zargar, 2021)	Need large amount of calculation (Ergen and Kozat, 2017)

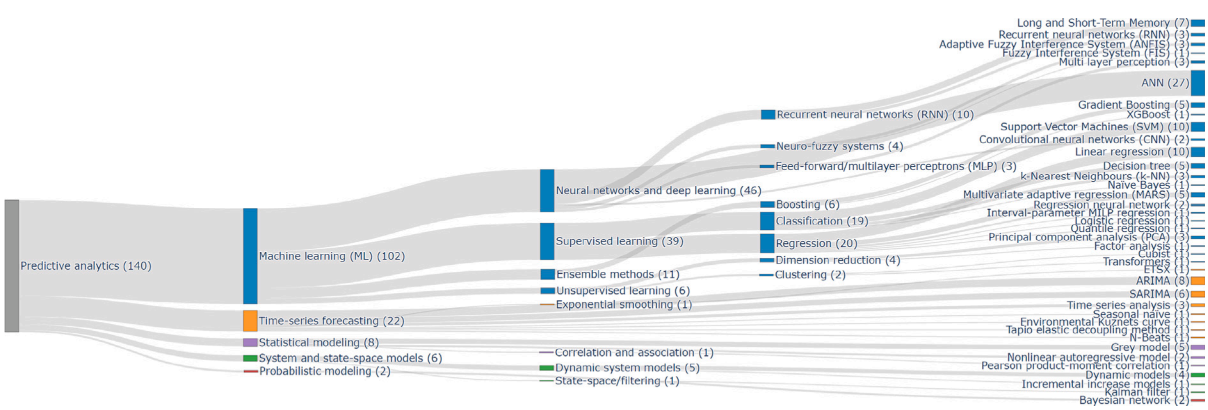

Fig. 3. Classification of the prediction models used for MSW production based on the literature review.

15 most frequently applied state variables per method. The number of applications and the best R^2 value for each method are given in parentheses.

Fig. 4 shows that artificial neural networks (ANN) (Wu et al., 2020) were used in 19.3% of all studies as the most common modeling technique. The second most frequently used methods are the Support Vector Machine (SVM) (Noori et al., 2009a) and linear regression (Popli et al., 2021), which were used in 7.1% of the studies. ARIMA (Cubillos, 2020) method was identified with a frequency of 5.7%, LSTM of 5.0% (Tu et al., 2022), and SARIMA of 4.3% (Merelles et al., 2019), while the Multivariate adaptive regression, Random forest (Nguyen et al., 2021), Decision tree (Kannangara et al., 2018), Gray model (Pudcha et al., 2023) and Gradient Boosting (Singh and Uppaluri, 2023) with 3.6–3.6% respectively. Fig. 4 shows that MSW production, population, and MSW fraction were the most frequently used state variables.

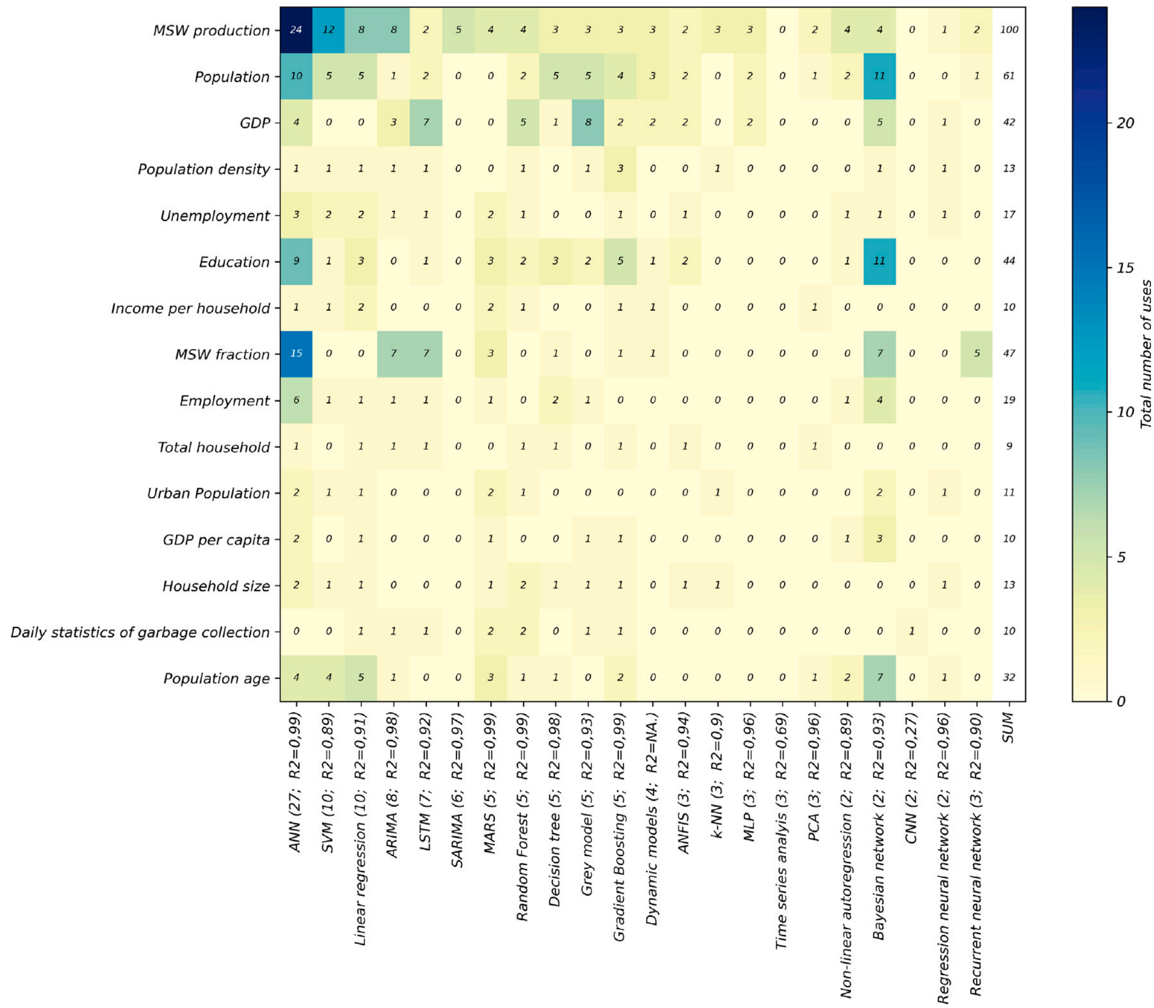

Fig. 4. Frequency of application and variables used in different models.

If we examine the model structures, state variables, and the amount of data used (number of observations), a recommendation system can be developed in the form of a decision tree (Fig. 5) that suggests the ideal model structure for the analyst based on the waste management task (goal) and available data. The numbers below the methods indicate the number of applications identified in the structured literature search. In this recommendation system: ARIMA model (Cubillos, 2020) with eight uses, the LSTM model (Tu et al., 2022) with seven uses, and the SARIMA model (Merelles et al., 2019) were used for forecasting in five cases. On the other hand, the multivariate adaptive regression, random forest (Nguyen et al., 2021), decision tree (Kannangara et al., 2018), gray model (Pudcha et al., 2023), and gradient boosting models (Singh and Uppaluri, 2023) were used in five cases each.

In Fig. 5 waste management analysis tasks are categorized by the colors of the methods (in the section marked with a yellow background), where tools suitable for strategic planning are highlighted in gray, tools recommended for supporting technological developments in green, and methods that partially support both aspects in yellow. The present study proposes a structured and data-driven framework to inform strategic decision-making in the domain of municipal solid waste (MSW) management. The proposed framework is designed to guide the selection of predictive methods that are tailored to specific policy and technological objectives.

As illustrated in Fig. 5, the methods under consideration are represented in the form of a decision tree. The categorization of groups is determined by the number of variables used, few (< 3), medium (3–7), and multivariate (> 7) groups can be distinguished. The second level is intended to separate the number of observations, which can be sparse (< 22), medium-term (22–162) and long-term (> 162). These threshold values for the decision levels (cutoff points) in the decision tree were determined during the training process, where the decision tree classifier was trained with data from the models included in the literature review.

It is also worth examining data generation patterns, as technological or strategic decision support models require data series with different temporal resolutions. The characteristics of the data series of the explored studies are summarized in Fig. 6.

Fig. 6 provides a concise visualization of the data's median, range, and presence of outliers in a single image. Upon examining Fig. 6, it is evident that the majority of the data is derived from daily collections. The 90-day data set represents the smallest extreme value, while the largest is a dataset collected over 28 years (Chung, 2010). The model constructed from the daily data collection was based solely on the total or partial waste fractions of the collected municipal solid waste.

Similar patterns were observed in the weekly and monthly data sets. In annual terms, the descriptive and predictive model is built using weekly data spanning between 4 (Jalali and Nouri, 2008) and 12 years (Johnson et al., 2017), and monthly data spanning between 3 (Nguyen et al., 2021) and 22 years (Abbasi et al., 2019). The variables show mixed results, with some variables predicting a longer period and others predicting a shorter time period. For monthly data, the longest period is 22 years with only 1 variable, while the shortest period is 3 years with 9 model variables. In contrast, the relationship for the weekly data is completely opposite. Many variables are associated

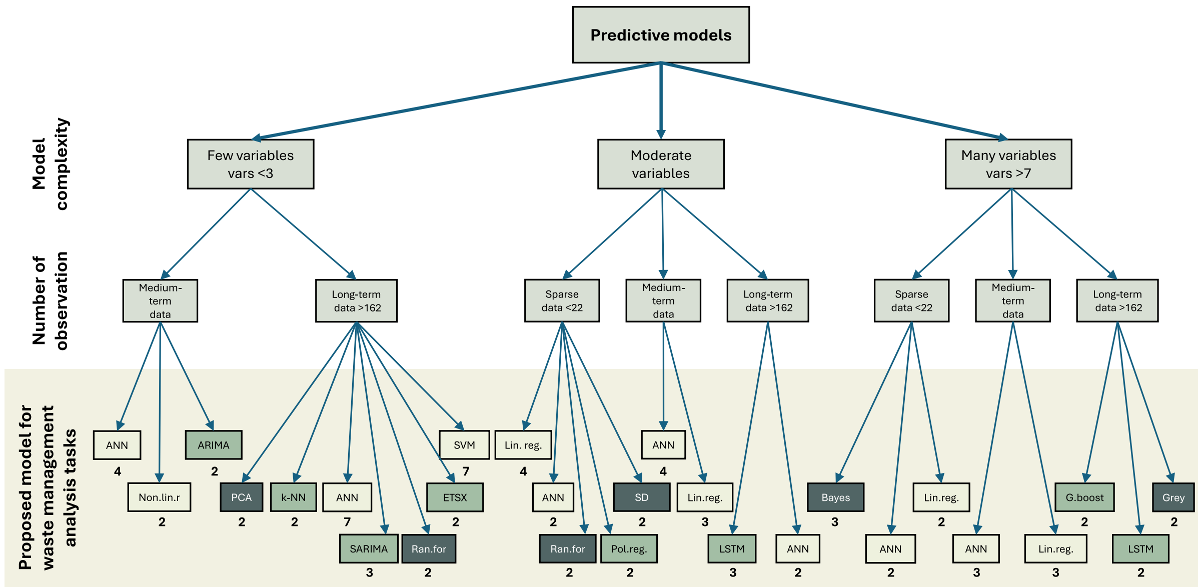

Fig. 5. Decision tree for model selection based on waste management analysis task, data source and number of observations.

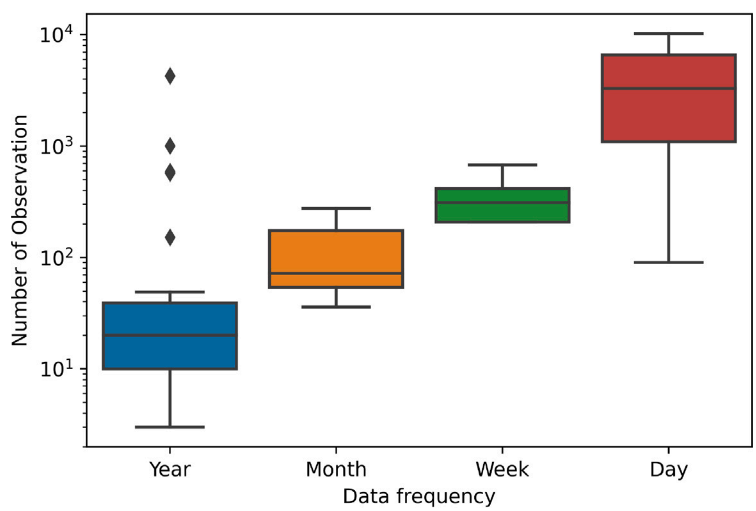

Fig. 6. Box plot for evaluation of data frequency of waste prediction methods.

with the longest period, while only one variable is associated with the shortest evaluation time interval. When examining the annual data, several interesting observations can be formulated. The upper extreme value of the plot is in the order of thousands, indicating that data has been collected for thousands of years. The upper limit of the set is 49 (Ebrahimi et al., 2012), meaning that the model was built using data from 49 years. For larger numbers, regional data was added to supplement the period and increase the number of observations for the entire area. The largest observation included 15 years of data from 285 cities (Wang et al., 2021). Enriching the model with data from the same period, but collected in a different area, is a common procedure in this kind of analysis task (Sebestyén et al., 2019). In contrast to previous variable data, however, more variables were used in each case. This is also due to the fact that annual data is among the most accessible. The fewest variables used were 5, and the most were 81. This distribution also shows that the choice of proxy variables and their methodological support in municipal solid waste predicting requires further research. To support the filling of this research gap, the proxy variables of the explored studies were grouped, which is shown in Fig. 7.

The municipal solid waste system was modeled using 455 variables in the explored 78 articles. Although many of these variables were identical, after a data cleaning the variables were grouped into six distinct sets, which can be described as follows (Fig. 7):

Economics: Variables were collected and accounted for in the largest set, which consisted of 140 of 455 variables. It comprises variables describing economic performance, such as the GDP (Adamović et al., 2017) of the country (Ghinea et al., 2016) or smaller area (Estay-Ossandon and Mena-Nieto, 2018), as well as specific indicators of it, e.g. tax revenue (Guo et al., 2022), exports of goods and services (Puntarić et al., 2022), and number of companies (Hoy et al., 2022).

Demography: This second largest set includes variables such as number of family members (Kumar and Samadder, 2017), number of household (Yang et al., 2022), population age groups (Johnson et al., 2017), and other population-related variables.

Waste: It is the third largest group, which consists of indicators related to waste. All of the explored 78 scientific papers examine the amount of municipal solid waste, in addition to which proxy variables (87 pcs.) such as inert waste (Singh and Satija, 2016), glass waste (Ahmed et al., 2022), textile waste (Ebrahimi et al., 2012), plastic waste (Adeleke et al., 2021) can be identified. It can be observed

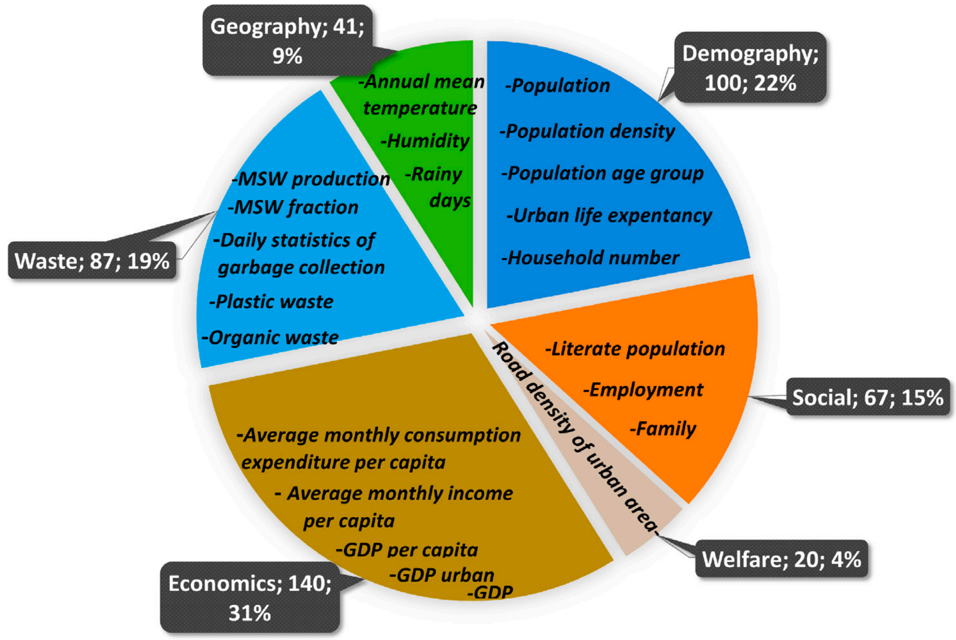

Fig. 7. Distribution of the proxy variables of MSW prediction models and the most frequently used variables.

that specific variables, like MSW/capita (Younes et al., 2015) are also included in this category.

These three groups constitute 72% of the total set of proxy variables, while the remaining 28% is accounted for by the next three groups (see Fig. 7).

Social: A separate group was created for social variables including employment, unemployment, education (for both men and women) (Abbasi et al., 2019), and urban poverty incidence.

Geography: It comprises geographic variables, including both general and specific characteristics that may not be equally applicable to all areas but can enhance the reliability of the prediction models. For instance, annual mean temperature (Wang et al., 2021), wind speed (Vu et al., 2022), and solar radiation (Adeogba et al., 2019).

Welfare: This is the smallest category, which comprises variables that could be described as social or economic, but are more indicative of welfare characteristics and emphasize commonalities. This category includes street cleaning area (Liu et al., 2021), number of hotel guests (Coskuner et al., 2021), and urban residents' expenditure on vegetables (Lu et al., 2022).

As it was presented above, how the number of observations developed in the MSW papers (Fig. 6), the issue of proxy variable selection was also highlighted (Fig. 7). These two basic model identification issues can be summarized in a modeling problem space, which is presented in Fig. 8.

Fig. 8 illustrates the relationship between the number of observations and the number of variables used in municipal solid waste (MSW) predicting models. This distribution offers valuable insights into the intended application of different modeling approaches. Models located on the upper end of the vertical axis, which utilize a large number of observations with relatively few variables, are particularly well-suited for technology-oriented predicting tasks. These include operational planning, such as route optimization or facility utilization estimation, where the primary goal is short-term accuracy supported by robust time-series data. Conversely, models on the far right of the horizontal axis employ a high number of variables and are typically used for strategic planning purposes. These models integrate complex socio-economic, demographic, and geographic factors to inform long-term decisions such as decarbonization roadmaps or infrastructure investments. The models located within the highlighted gray region represent an optimal balance. They incorporate a sufficiently large set of variables and observations, making them applicable for both strategic and technological predicting needs. On the other hand, models found in the lower-left corner of the figure, characterized by low observation counts and few variables, are limited in their predictive power. These models are more appropriate for comparative assessments, scenario testing, or early-stage estimations, rather than for building highly accurate predicting tools. As such, the selection of predicting methodology should be informed by both data availability and the specific decision-making context in which the model will be applied.

4. Discussion

The findings are interpreted within a broader analytical and interpretative framework, demonstrating how models associated with different data resolutions and methodological families can be adapted and operationalized to meet both short-term (operational) and long-term (strategic) decision-making requirements in municipal solid waste (MSW) management. Accordingly, the discussion emphasizes the key trade-offs arising from data availability, proxy-variable selection, spatio-temporal scaling (local seasonality versus the inclusion of regional datasets), and the implications of a dynamically evolving regulatory context.

Building on these insights, this literature review introduces a structured, data-driven framework to support technology-related and strategic decision-making in MSW management. A novel model selection framework was developed (Fig. 5), which is intended to guide the selection of forecasting methods in a manner that is explicitly aligned with both policy-oriented and technology-oriented objectives. Its utility is particularly salient in long-term planning and system optimization contexts, where forecasting accuracy and interpretability are critical. At the strategic level, the framework can inform decarbonization and energy-balance assessments, waste-quantity reduction pathways, improvements in recycling and circularity performance, awareness-raising through education and dissemination, and evaluations of compliance with environmental legislation. From a technological and operational standpoint, the proposed methodology underpins key design and implementation decisions, including route optimization, facility capacity planning, technology selection, reverse supply chain configuration, and

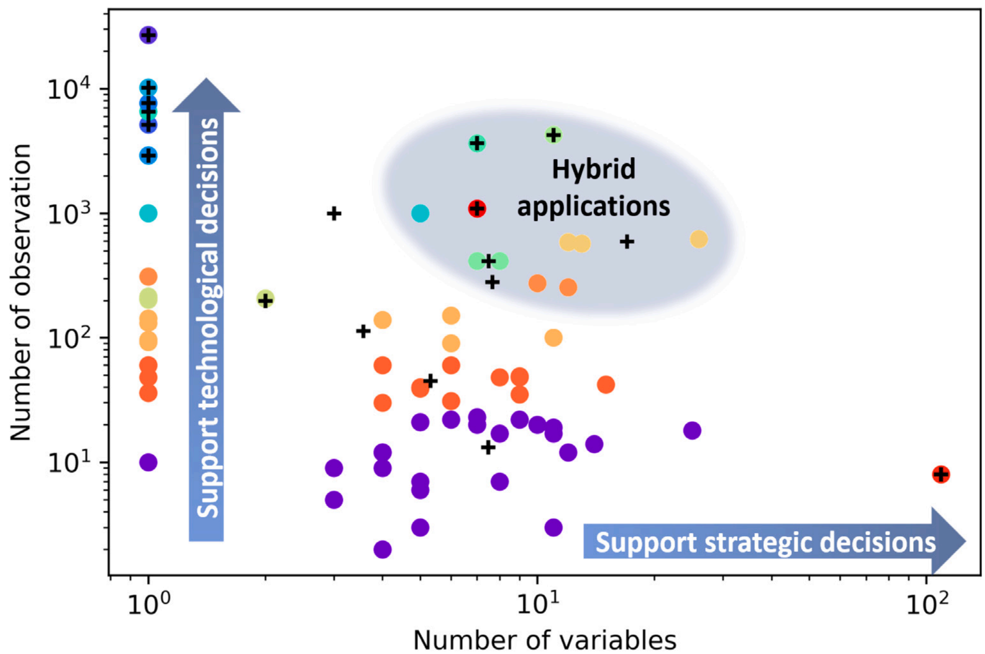

Fig. 8. MSW modeling problem space: model structures for technology-related or strategy-related issues according to the number of observations and the number of proxy variables.

scheduling that reflects energy-demand profiles. The primary contribution, therefore, lies in systematically linking the choice of forecasting model structures to heterogeneous, practice-driven objectives, thereby supporting the development of adaptive, efficient, and target-oriented municipal solid waste management systems.

The relevance of this alignment is reinforced by the role of data frequency in model applicability. Fig. 6 presents the distribution of data frequencies used in MSW forecasting, categorized by daily, weekly, monthly, and annual temporal resolution. As frequency increases, the number of observations rises substantially, with daily datasets providing the most granular and extensive input for model development. This variation materially influences the intended use of forecasting models. High-resolution daily datasets — typically derived from operational indicators such as container fill-level measurements or vehicle collection logs — are well suited to short-term forecasting needs central to technology-focused planning, including route optimization, scheduling, and capacity management. Conversely, lower-frequency annual data are more appropriate for strategic forecasting tasks, such as identifying long-term trends, establishing decarbonization targets, and evaluating compliance with waste-management directives. Collectively, these distinctions indicate that each frequency level affords different modeling opportunities and constraints, underscoring the importance of matching data granularity to the forecasting purpose, whether operational or strategic.

Within strategic forecasting, the inclusion of a broad and heterogeneous set of explanatory variables (Fig. 7) is critical for constructing robust, informative, and generalizable models. Economic, well-being, social, demographic, geographic, and waste-related determinants contribute through different causal pathways and thus jointly enhance the explanatory depth of forecasting systems. A more diverse data foundation supports complex planning applications such as decarbonization strategies, infrastructure scaling, and policy-compliance assessment. Moreover, for supervised learning, proxy variables should be paired with observed MSW measurements to enable rigorous model training and validation. While forecasting models can also be developed from exclusively waste-related datasets — as discussed in the preceding section — this approach is more commonly associated with operational and technology-oriented tasks, such as optimizing collection schedules or maximizing facility utilization. In such contexts, long-term time series data are required to capture recurring patterns and seasonal effects reliably. These data-driven models can thereby directly facilitate technological development and enhance operational efficiency in MSW systems.

While the proposed model-structure recommendation framework supports the identification of models capable of predicting changes in MSW quantities, forecasting qualitative (composition) changes remains an open research task. Addressing this gap would enable the “ex ante” identification of treatment-technology adjustments (Farahbakhsh et al., 2023), but it is inherently challenging due to strong dependence on data availability, as highlighted in this study. Although national waste management strategies can be informed using national, annual datasets, technological development and implementation require explicit accounting for local characteristics and seasonality (Denafas et al., 2014). This, in turn, necessitates monthly or higher-resolution data at the level of cities or collection districts. Accordingly, the proposed framework should be viewed as a robust starting point for further knowledge development in MSW forecasting, while recognizing that the most appropriate proxy-variable sets are likely to vary across countries and regions, therefore, model identification and interpretation cannot be meaningfully performed without domain expert input.

In terms of model performance evaluation, 44 studies reported the coefficient of determination (R^2) (ranging from 0.53 to 0.99996), 37 presented the root mean square error (RMSE) (ranging from 0.003 to 2,305,544), and 25 reported the mean absolute percentage error (MAPE) (ranging from 0.008 to 25.7). Accuracy was reported in only two studies (values of 0.87 and 0.991). Several methodological limitations can be identified in relation to these performance measures. R^2 quantifies the proportion of variance explained by the model. However, it does not capture structural errors, such as systematic under- or overestimation, nor does it necessarily reflect the model’s ability to represent nonlinear patterns. Furthermore, R^2 is data-dependent and therefore not always comparable across datasets. RMSE expresses deviations in absolute units, which limits its interpretability unless the scale or range of the target variable and the magnitude of measurement noise are explicitly characterized. Although MAPE is scale-independent and, in principle, easier to interpret, its practical utility is reduced when reporting conventions are unclear: several studies do not explicitly indicate whether MAPE values are provided as ratios (e.g., 0.12) or as percentages (12%).

To enable a more comprehensive and discriminative assessment — particularly for classification tasks — more informative performance metrics are recommended. Accuracy captures the fraction of correct predictions over all observations, precision (positive predictive value) quantifies the proportion of predicted positive cases that are truly positive, and recall (sensitivity) measures the proportion of actual positive cases correctly identified. The F1-score, defined as the harmonic mean of precision and recall, summarizes their trade-off in a single measure. These metrics are derived from the confusion matrix, which organizes correct (TP, TN) and incorrect (FP, FN) classifications, and they provide richer diagnostic insight by reflecting not only the magnitude of errors but also their type and direction, while being less sensitive to class imbalance than accuracy alone.

Finally, cross-validation (e.g. k-fold cross-validation) is widely used to enhance the robustness and reliability of performance estimates. In this procedure, the dataset is partitioned into multiple approximately equal subsets, and the model is trained and evaluated iteratively across folds, averaging performance over folds yields a more stable and less biased estimate of expected generalization performance. This approach reduces the risk of overfitting and enables more objective comparisons of model performance across datasets and study settings.

An additional priority is to quantify the system-level effects induced by dynamically changing legal and regulatory requirements (Awino and Apitz, 2024). Achieving this requires the integration of forecasting outputs with technological and infrastructural information, including the disaggregated modeling and analysis of individual waste fractions. Such an approach enables higher-level implementation and can strengthen the sustainability and resilience of municipal solid waste management systems. Although this review paper establishes foundational elements of this direction in a gap-filling manner, effective decision support still depends on the continued advancement of data-driven models. A key limitation of the proposed framework is that it does not evaluate predictive accuracy, instead, it focuses on recommending suitable model structures for specific MSW analysis tasks conditional on the available data.

5. Conclusions

The ever-increasing volume of municipal solid waste and the dynamically changing legal environment presents serious challenges to waste management decision-makers. Waste treatment technological changes and development investments demand high-level and reliable performance of MSW predicting tasks, for which different artificial intelligence-supported models can be identified.

In this literature review, 78 scientific publications were explored in detail by querying the Scopus database according to the PRISMA methodology, based on which 36 different AI-driven models and 455 proxy variables were identified as possible elements for model building. The choice of model structures depends on the range of data and proxy variables chosen by the analyst to optimize model accuracy. To support this, we integrated previous models into a model structure recommendation system based on the goal-oriented municipal solid waste management analysis tasks and dataset availability, has been developed.

It can be concluded that from models with a simpler structure with a high number of daily observations to more complex models supported by several proxy variables relying mainly on annual data for the prediction of MSW, artificial neural networks (ANN) are the most commonly used models. Other common tools are support vector machine (SVM), autoregressive integrated moving average (ARIMA), long short-term memory (LSTM) and regression models. Most prediction models use MSW production and fraction data, population, population density, GDP, household income, education and unemployment ratio as proxy variables. To increase the accuracy of the models, the proxy variables must be chosen adequately, in addition to waste-related variables, demographic, economic, social, geographic and welfare variables can be used.

The framework supporting the selection of the model structure for MSW quantity prediction that we propose contributes to the optimal determination of the model structures, however, the prediction of changes in the quality of MSW, including modeling separated by waste fractions and the prediction of specific technological changes, is a task to be solved for a sustainable and resilient municipal solid waste management sector.

Since data-driven and AI solutions are developing at an incredible speed, the authors recommend continuous testing of the applicability of new models and continuous knowledge integration into waste management analysis tasks, for which we recommend that the development of model structures (strategic models or technological models) be based on the methodology presented in this review paper.

CRediT authorship contribution statement

Róbert Fejes: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Róbert Kurdi:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Viktor Sebestyén:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

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Appendix A. Supplementary data

Model pool revealed based on the literature research presented in Section 2.

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.rcradv.2025.200310.

Data availability

Data will be made available on request.

References

Abbasi, M., El Hanandeh, A., 2016. Forecasting municipal solid waste generation using artificial intelligence modelling approaches. Waste Manage. 56, 13–22.

Abbasi, M., Rastgoo, M.N., Nakisa, B., 2019. Monthly and seasonal modeling of municipal waste generation using radial basis function neural network. Environ. Prog. Sustain. Energy 38 (3), e13033.

Abdallah, M., Talib, M.A., Feroz, S., Nasir, Q., Abdalla, H., Mahfood, B., 2020. Artificial intelligence applications in solid waste management: A systematic research review. Waste Manage. 109, 231–246.

Abdullah, D.M., Abdulazeez, A.M., 2021. Machine learning applications based on SVM classification a review. Qubahan Acad. J. 1 (2), 81–90.

Adamović, V.M., Antanasijević, D.Z., Ristić, M.Đ., Perić-Grujić, A.A., Pocajt, V.V., 2017. Prediction of municipal solid waste generation using artificial neural network approach enhanced by structural break analysis. Environ. Sci. Pollut. Res. 24 (1), 299–311.

Adams, S.O., Bamanga, M.A., 2020. Modelling and forecasting seasonal behavior of rainfall in Abuja, Nigeria; A SARIMA approach. Am. J. Math. Stat 10 (1), 10–19.

Adeleke, O., Akinlabi, S.A., Jen, T.C., Dunmade, I., 2021. Application of artificial neural networks for predicting the physical composition of municipal solid waste: An assessment of the impact of seasonal variation. Waste Manag. Res. 39 (8), 1058–1068.

Adeleke, O., Akinlabi, S.A., Jen, T.C., Dunmade, I., 2022. Prediction of municipal solid waste generation: an investigation of the effect of clustering techniques and parameters on ANFIS model performance. Environ. Technol. 43 (11), 1634–1647.

Adeogba, E., Barty, P., O'Dwyer, E., Guo, M., 2019. Waste-to-resource transformation: gradient boosting modeling for organic fraction municipal solid waste projection. ACS Sustain. Chem. Eng. 7 (12), 10460–10466.

Aghdam, E., Mohandes, S.R., Manu, P., Cheung, C., Yunusa-Kaltungo, A., Zayed, T., 2023. Predicting quality parameters of wastewater treatment plants using artificial intelligence techniques. J. Clean. Prod. 405, 137019.

Ahmed, A.K.A., Ibraheem, A.M., Abd-Ellah, M.K., 2022. Forecasting of municipal solid waste multi-classification by using time-series deep learning depending on the living standard. Results Eng. 16, 100655.

Aigner, S., Körner, M., 2020. The importance of loss functions for increasing the generalization abilities of a deep learning-based next frame prediction model for traffic scenes. Mach. Learn. Knowl. Extr. 2 (2), 6.

Al-Mahasneh, M., Aljarrah, M., Rababah, T., Alu'datt, M., 2016. Application of hybrid neural fuzzy system (ANFIS) in food processing and technology. Food Eng. Rev. 8, 351–366.

Almassri, A.M., Wan Hasan, W.Z., Ahmad, S.A., Shafie, S., Wada, C., Horio, K., 2018. Self-calibration algorithm for a pressure sensor with a real-time approach based on an artificial neural network. Sensors 18 (8), 2561.

Alzamora, B.R., de Vasconcelos Barros, R.T., de Oliveira, L.K., Gonçalves, S.S., 2022. Forecasting and the influence of socioeconomic factors on municipal solid waste generation: A literature review. Environ. Dev. 44, 100734.

Assembly, G., 2015. Sustainable development goals. SDGs Transform. Our World 2030 (10.1186).

Awino, F.B., Apitz, S.E., 2024. Solid waste management in the context of the waste hierarchy and circular economy frameworks: An international critical review. Integr. Environ. Assess. Manag. 20 (1), 9–35.

Ayeleru, O., Fajimi, L., Oboirien, B., Olubambi, P., 2021. Forecasting municipal solid waste quantity using artificial neural network and supported vector machine techniques: A case study of Johannesburg, South Africa. J. Clean. Prod. 289, 125671.

Ben-Hur, A., Ong, C.S., Sonnenburg, S., Schölkopf, B., Rätsch, G., 2008. Support vector machines and kernels for computational biology. PLoS Comput. Biol. 4 (10), e1000173.

Binder, M., Moosbauer, J., Thomas, J., Bischl, B., 2020. Multi-objective hyperparameter tuning and feature selection using filter ensembles. In: Proceedings of the 2020 Genetic and Evolutionary Computation Conference. pp. 471–479.

Bonano, E.J., Hora, S.C., Keeney, R.L., Von Winterfeldt, D., 1990. Elicitation and Use of Expert Judgment in Performance Assessment for High-Level Radioactive Waste Repositories. Technical Report, Nuclear Regulatory Commission, Washington, DC (USA). Div. of High-Level ....

Brophy, J., Hammoudeh, Z., Lowd, D., 2023. Adapting and evaluating influence-estimation methods for gradient-boosted decision trees. J. Mach. Learn. Res. 24 (154), 1–48.

Cai, P.T., Chen, T., Chen, B., Wang, Y.C., Ma, Z.Y., Yan, J.H., 2023. The impact of pollutant emissions from co-incineration of industrial waste in municipal solid waste incinerators. Fuel 352, 129027.

Çankaya, S., Abacı, S.H., 2015. A comparative study of some estimation methods in simple linear regression model for different sample sizes in presence of outliers. Turk. J. Agriculture-Food Sci. Technol. 3 (6), 380–386.

Chung, S.S., 2010. Projecting municipal solid waste: The case of Hong Kong SAR. Resour. Conserv. Recycl. 54 (11), 759–768.

Coskuner, G., Jassim, M.S., Zontul, M., Karateke, S., 2021. Application of artificial intelligence neural network modeling to predict the generation of domestic, commercial and construction wastes. Waste Manag. Res. 39 (3), 499–507.

Cubillos, M., 2020. Multi-site household waste generation forecasting using a deep learning approach. Waste Manage. 115, 8–14.

Dao, D.V., Adeli, H., Ly, H.B., Le, L.M., Le, V.M., Le, T.T., Pham, B.T., 2020. A sensitivity and robustness analysis of GPR and ANN for high-performance concrete compressive strength prediction using a Monte Carlo simulation. Sustainability 12 (3), 830.

Denafas, G., Ruzgas, T., Martuzevičius, D., Shmarin, S., Hoffmann, M., Mykhaylenko, V., Ogorodnik, S., Romanov, M., Neguliaeva, E., Chusov, A., et al., 2014. Seasonal variation of municipal solid waste generation and composition in four east European cities. Resour. Conserv. Recycl. 89, 22–30.

Dou, B., Zhu, Z., Merkurjev, E., Ke, L., Chen, L., Jiang, J., Zhu, Y., Liu, J., Zhang, B., Wei, G.W., 2023. Machine learning methods for small data challenges in molecular science. Chem. Rev. 123 (13), 8736–8780.

Dubey, A.K., Kumar, A., García-Díaz, V., Sharma, A.K., Kanhaiya, K., 2021. Study and analysis of SARIMA and LSTM in forecasting time series data. Sustain. Energy Technol. Assessments 47, 101474.

Dyson, B., Chang, N.B., 2005. Forecasting municipal solid waste generation in a fast-growing urban region with system dynamics modeling. Waste Manage. 25 (7), 669–679.

Ebrahimi, A., Amin, M.M., Bina, B., Mokhtari, M., Alaghebandan, H.R., Samaei, M.R., Hashemi, H., 2012. Prediction of the energy content of the municipal solid waste. Int. J. Environ. Health Eng. 1 (December), 1–6.

Emmanuel, T., Maupong, T., Mpoeleng, D., Semong, T., Mphago, B., Tabona, O., 2021. A survey on missing data in machine learning. J. Big Data 8, 1–37.

Enemosah, A., 2025. Enhancing DevOps efficiency through AI-driven predictive models for continuous integration and deployment pipelines. Int. J. Res. Publ. Rev. 6 (1), 871–887.

Ergen, T., Kozat, S.S., 2017. Online training of LSTM networks in distributed systems for variable length data sequences. IEEE Trans. Neural Networks Learn. Syst. 29 (10), 5159–5165.

Eslami, S., Ng, K.T.W., Kabir, G., 2021. Prediction of waste disposal during COVID-19 using system dynamics modeling. In: Canadian Society of Civil Engineering Annual Conference. Springer, pp. 343–350.

Estay-Ossandon, C., Mena-Nieto, A., 2018. Modelling the driving forces of the municipal solid waste generation in touristic islands. A case study of the balearic islands (2000–2030). Waste Manage. 75, 70–81.

Eurostat, 2025. Database. https://ec.europa.eu/eurostat/databrowser/explore/all/all_themes. (Accessed 11 February 2025).

Fan, F.L., Xiong, J., Li, M., Wang, G., 2021. On interpretability of artificial neural networks: A survey. IEEE Trans. Radiat. Plasma Med. Sci. 5 (6), 741–760.

Fang, T., Lahdelma, R., 2016. Evaluation of a multiple linear regression model and SARIMA model in forecasting heat demand for district heating system. Appl. Energy 179, 544–552.

Farahbakhsh, S., Snellinx, S., Mertens, A., Belderbos, E., Bourgeois, L., Van Meensel, J., 2023. What's stopping the waste-treatment industry from adopting emerging circular technologies? An agent-based model revealing drivers and barriers. Resour. Conserv. Recycl. 190, 106792.

Fokker, E., Koch, T., Dugundji, E.R., 2023. Short-term time series forecasting for multi-site municipal solid waste management. Procedia Comput. Sci. 220, 170–179.

Genuer, R., 2012. Variance reduction in purely random forests. J. Nonparametr. Stat. 24 (3), 543–562.

Ghinea, C., Drăgoi, E.N., Comăniţă, E.D., Gavrilescu, M., Câmpean, T., Curteanu, S., Gavrilescu, M., 2016. Forecasting municipal solid waste generation using prognostic tools and regression analysis. J. Environ. Manag. 182, 80–93.

Golbraikh, A., Shen, M., Xiao, Z., Xiao, Y.D., Lee, K.H., Tropsha, A., 2003. Rational selection of training and test sets for the development of validated QSAR models. J. Comput. Aided Mol. Des. 17, 241–253.

Gudivada, V., Apon, A., Ding, J., 2017. Data quality considerations for big data and machine learning: Going beyond data cleaning and transformations. Int. J. Adv. Softw. 10 (1), 1–20.

Guo, R., Liu, H.M., Sun, H.H., Wang, D., Yu, H., Do Rosario Alves, D., Yao, L., 2022. Forecasting of municipal solid waste generation in China based on an optimized grey multiple regression model. J. Mater. Cycles Waste Manag. 24 (6), 2314–2327.

Hall, M.A., 2000. Correlation-based feature selection of discrete and numeric class machine learning.

Hao, D., Zhang, L., Sumkin, J., Mohamed, A., Wu, S., 2020. Inaccurate labels in weakly-supervised deep learning: Automatic identification and correction and their impact on classification performance. IEEE J. Biomed. Health Informatics 24 (9), 2701–2710.

Hoornweg, D., Bhada-Tata, P., 2012. What a Waste: A Global Review of Solid Waste Management. World Bank, Washington, DC.

Hoy, Z.X., Woon, K.S., Chin, W.C., Hashim, H., Van Fan, Y., 2022. Forecasting heterogeneous municipal solid waste generation via Bayesian-optimised neural network with ensemble learning for improved generalisation. Comput. Chem. Eng. 166, 107946.

Ilic, I., Görgülü, B., Cevik, M., Baydoğan, M.G., 2021. Explainable boosted linear regression for time series forecasting. Pattern Recognit. 120, 108144.

Izquierdo-Horna, L., Kahhat, R., Vázquez-Rowe, I., 2022. Reviewing the influence of sociocultural, environmental and economic variables to forecast municipal solid waste (MSW) generation. Sustain. Prod. Consum. 33, 809–819.

Jalali, G.Z.M., Nouri, R.E., 2008. Prediction of municipal solid waste generation by use of artificial neural network: A case study of mashhad. Int. J. Environ. Res..
Jang, H., Jeong, Y., Yoon, B., 2021. TechWord: Development of a technology lexical database for structuring textual technology information based on natural language processing. Expert Syst. Appl. 164, 114042.
Jin, R., Agrawal, G., 2003. Efficient decision tree construction on streaming data. In: Proceedings of the Ninth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. pp. 571–576.
Johnson, N.E., Ianiuk, O., Cazap, D., Liu, L., Starobin, D., Dobler, G., Ghandehari, M., 2017. Patterns of waste generation: A gradient boosting model for short-term waste prediction in new york city. Waste Manage. 62, 3–11.
Kannangara, M., Dua, R., Ahmadi, L., Bensebaa, F., 2018. Modeling and prediction of regional municipal solid waste generation and diversion in Canada using machine learning approaches. Waste Manage. 74, 3–15.
Karimi, D., Dou, H., Warfield, S.K., Gholipour, A., 2020. Deep learning with noisy labels: Exploring techniques and remedies in medical image analysis. Med. Image Anal. 65, 101759.
Kaur, A., Bharti, R., Sharma, R., 2023. Municipal solid waste as a source of energy. Mater. Today: Proc. 81, 904–915.
Kaza, S., Yao, L., Bhada-Tata, P., Van Woerden, F., 2018. What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050. World Bank Publications.
Khajevand, N., Tehrani, R., 2019. Impact of population change and unemployment rate on Philadelphia's waste disposal. Waste Manage. 100, 278–286.
Khanal, A., 2023. Forecasting municipal solid waste generation using linear regression analysis: A case of Kathmandu Metropolitan city, Nepal. Multidiscip. Sci. J. 5 (2), 2023019–2023019.
Khashei, M., Bijari, M., 2011. A novel hybridization of artificial neural networks and ARIMA models for time series forecasting. Appl. Soft Comput. 11 (2), 2664–2675.
Khoshgoftaar, T.M., Allen, E.B., 2001. Controlling overfitting in classification-tree models of software quality. Empir. Softw. Eng. 6, 59–79.
Kolawole, T.O., Iyiola, O., Ibrahim, H., Isibor, R.A., 2023. Contamination, ecological and health risk assessments of potentially toxic elements in soil around a municipal solid waste disposal facility in southwestern Nigeria. J. Trace Elements Miner. 5, 100083.
Kovačević, L., Gaudelet, T., Opzoomer, J., Triendl, H., Whittaker, J., Uhler, C., Edwards, L., Taylor-King, J.P., 2025. No foundations without foundations–why semi-mechanistic models are essential for regulatory biology. arXiv preprint arXiv:2501.19178.
Kulisz, M., Kujawska, J., 2020. Prediction of municipal waste generation in Poland using neural network modeling. Sustainability 12 (23), 10088.
Kumar, S., Gaur, A., Kamal, N., Pathak, M., Shrinivas, K., Singh, P., 2020. Artificial neural network based optimum scheduling and management of forecasting municipal solid waste generation–case study: Greater Noida in Uttar Pradesh (India). J. Phys.: Conf. Ser. 1478 (1), 012033.
Kumar, A., Samadder, S., 2017. An empirical model for prediction of household solid waste generation rate–A case study of Dhanbad, India. Waste Manage. 68, 3–15.
Lee, N.U., Shim, J.S., Ju, Y.W., Park, S.C., 2018. Design and implementation of the SARIMA–SVM time series analysis algorithm for the improvement of atmospheric environment forecast accuracy. Soft Comput. 22, 4275–4281.
Likotiko, E., Matsuda, Y., Yasumoto, K., 2020. Smart garbage bin: Garbage growth behavior prediction. In: The 28th Multimedia Communication and Distributed Processing System Workshop. DPSWS'20, pp. 27–33.
Liu, X., Gao, C., Li, P., 2012. A comparative analysis of support vector machines and extreme learning machines. Neural Netw. 33, 58–66.
Liu, B., Zhang, L., Wang, Q., 2021. Demand gap analysis of municipal solid waste landfill in Beijing: Based on the municipal solid waste generation. Waste Manage. 134, 42–51.
Lu, W., Huo, W., Gulina, H., Pan, C., 2022. Development of machine learning multi-city model for municipal solid waste generation prediction. Front. Environ. Sci. Eng. 16 (9), 119.
Maalouf, A., Mavropoulos, A., 2023. Re-assessing global municipal solid waste generation. Waste Manag. Res. 41 (4), 936–947.
Mahesh, B., 2020. Machine learning algorithms-a review. Int. J. Sci. Res. (IJSR).[Internet] 9 (1), 381–386.
Maiya, A.S., 2022. Ktrain: A low-code library for augmented machine learning. J. Mach. Learn. Res. 23 (158), 1–6.
Maiyar, L.M., Ramanathan, R., Swamy, S.L.B.N., Ramanathan, U., 2023. Fighting food waste: How can artificial intelligence and analytics help? In: Innovation Analytics: Tools for Competitive Advantage. World Scientific, pp. 171–189.
Majchrowska, S., Mikołajczyk, A., Ferlin, M., Klawikowska, Z., Plantykow, M.A., Kwasigroch, A., Majek, K., 2022. Deep learning-based waste detection in natural and urban environments. Waste Manage. 138, 274–284.
Mandal, A., Leavy, S., Little, S., 2021. Dataset diversity: measuring and mitigating geographical bias in image search and retrieval.
Marandi, F., Ghomi, S.F., 2016. Time series forecasting and analysis of municipal solid waste generation in Tehran city. In: 2016 12th International Conference on Industrial Engineering. ICIE, IEEE, pp. 14–18.
Merelles, L.R.d., Silva, C.d.O., Luz, M.P.d., Menezes, J.E.d., Dias, V.d., 2019. Forecasting of solid waste generation for the Aparecida de Goiania (GO), Brazil, landfill by time series. Eng. Sanit. E Ambient. 24, 537–546.
Meyer, D.E., Li, M., Ingwersen, W.W., 2020. Analyzing economy-scale solid waste generation using the United States environmentally-extended input-output model. Resour. Conserv. Recycl. 157, 104795.
Meza, J.K.S., Yepes, D.O., Rodrigo-Ilarri, J., Cassiraga, E., 2019. Predictive analysis of urban waste generation for the city of Bogotá, Colombia, through the implementation of decision trees-based machine learning, support vector machines and artificial neural networks. Heliyon 5 (11).
Mohammadiun, S., Hu, G., Gharahbagh, A.A., Li, J., Hewage, K., Sadiq, R., 2022. Evaluation of machine learning techniques to select marine oil spill response methods under small-sized dataset conditions. J. Hazard. Mater. 436, 129282.
Moher, D., Shamseer, L., Clarke, M., Ghersi, D., Liberati, A., Petticrew, M., Shekelle, P., Stewart, L.A., Group, P.P., 2015. Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement. Syst. Rev. 4, 1–9.
Mondal, P., Shit, L., Goswami, S., 2014. Study of effectiveness of time series modeling (ARIMA) in forecasting stock prices. Int. J. Comput. Sci. Eng. Appl. 4 (2), 13.
Mor, S., Ravindra, K., 2023. Municipal solid waste landfills in lower-and middle-income countries: Environmental impacts, challenges and sustainable management practices. Process. Saf. Environ. Prot..
Navarro-Esbrı, J., Diamadopoulos, E., Ginestar, D., 2002. Time series analysis and forecasting techniques for municipal solid waste management. Resour. Conserv. Recycl. 35 (3), 201–214.
Ngo, V.D., Vuong, T.C., Van Luong, T., Tran, H., 2024. Machine learning-based intrusion detection: feature selection versus feature extraction. Clust. Comput. 27 (3), 2365–2379.
Nguyen, T.T., Luu, T.T., Tong, P.T.A., 2024. Fine-tuning DETR: Toward holistic process in plastic waste sorting system. Waste Manage. 179, 154–162.
Nguyen, X.C., Nguyen, T.T.H., La, D.D., Kumar, G., Rene, E.R., Nguyen, D.D., Chang, S.W., Chung, W.J., Nguyen, X.H., Nguyen, V.K., 2021. Development of machine learning-based models to forecast solid waste generation in residential areas: A case study from Vietnam. Resour. Conserv. Recycl. 167, 105381.
Noori, R., Abdoli, M., Ghasrodashti, A.A., Jalili Ghazizade, M., 2009a. Prediction of municipal solid waste generation with combination of support vector machine and principal component analysis: A case study of mashhad. Environ. Prog. Sustain. Energy: Off. Publ. Am. Inst. Chem. Eng. 28 (2), 249–258.
Noori, R., Abdoli, M., Ghazizade, M.J., Samieifard, R., 2009b. Comparison of neural network and principal component-regression analysis to predict the solid waste generation in Tehran. Iran. J. Publ. Health 38 (1), 74–84.
OECD, 2025. Data - trusted statistics supporting evidence-based policy. https://www.oecd.org/en/data/indicators.html?orderBy=mostRelevant&page=0. (Accessed 11 February 2025).
Pamukçu, H., Yapıcıoğlu, P.S., Yeşilnacar, M.İ., 2023. Investigating the mitigation of greenhouse gas emissions from municipal solid waste management using ant colony algorithm, Monte Carlo simulation and LCA approach in terms of EU green deal. Waste Manag. Bull. 1 (2), 6–14.
Pan, F., Converse, T., Ahn, D., Salvetti, F., Donato, G., 2009. Feature selection for ranking using boosted trees. In: Proceedings of the 18th ACM Conference on Information and Knowledge Management. pp. 2025–2028.
Popli, K., Park, C., Han, S.M., Kim, S., 2021. Prediction of solid waste generation rates in urban region of laos using socio-demographic and economic parameters with a multi linear regression approach. Sustainability 13 (6), 3038.
Pudcha, T., Phongphiphat, A., Wangyao, K., Towprayoon, S., 2023. Forecasting municipal solid waste generation in thailand with grey modelling.. Environ. Nat. Resour. J. 21 (1).
Puntarić, E., Pezo, L., Zgorelec, v., Gunjača, J., Kučić Grgić, D., Voća, N., 2022. Prediction of the production of separated municipal solid waste by artificial neural networks in Croatia and the European union. Sustainability 14 (16), 10133.
Razzaghi, T., Roderick, O., Safro, I., Marko, N., 2016. Multilevel weighted support vector machine for classification on healthcare data with missing values. PLoS One 11 (5), e0155119.
Revanna, J.K.C., Al-Nakash, N.Y.B., 2023. Metaheuristic link prediction (MLP) using AI based ACO-GA optimization model for solving vehicle routing problem. Int. J. Inf. Technol. 15 (7), 3425–3439.
Rimaitytė, I., Ruzgas, T., Denafas, G., Račys, V., Martuzevicius, D., 2012. Application and evaluation of forecasting methods for municipal solid waste generation in an eastern-European city. Waste Manag. Res. 30 (1), 89–98.
Rohlfs, C., 2023. Forbidden knowledge and specialized training: A versatile solution for the two main sources of overfitting in linear regression. Amer. Statist. 77 (2), 160–168.
Santos, P., Cervantes, G.C., Zaragoza-Benzal, A., Byrne, A., Karaca, F., Ferrández, D., Salles, A., Bragança, L., 2024. Circular material usage strategies and principles in buildings: A review. Buildings 14 (1), 281.
Schielzeth, H., 2010. Simple means to improve the interpretability of regression coefficients. Methods Ecol. Evol. 1 (2), 103–113.
Sebestyén, V., Bulla, M., Rédey, Á., Abonyi, J., 2019. Network model-based analysis of the goals, targets and indicators of sustainable development for strategic environmental assessment. J. Environ. Manag. 238, 126–135.
Seifi, A., Riahi-Madvar, H., 2019. Improving one-dimensional pollution dispersion modeling in rivers using ANFIS and ANN-based GA optimized models. Environ. Sci. Pollut. Res. 26, 867–885.

Sengeni, D., Padmapriya, G., Imambi, S.S., Suganthi, D., Suri, A., Boopathi, S., 2023. Biomedical waste handling method using artificial intelligence techniques. In: Handbook of Research on Safe Disposal Methods of Municipal Solid Wastes for a Sustainable Environment. IGI Global, pp. 306–323.
Shimizu, N., Kaneko, H., 2021. Constructing regression models with high prediction accuracy and interpretability based on decision tree and random forests. J. Comput. Chem. Jpn. 20 (2), 71–87.
Sin-Wai, C., 2023. Routledge Encyclopedia of Translation Technology. Taylor & Francis Group.
Singh, D., Satija, A., 2016. Municipal solid waste generation forecasting for faridabad city located in haryana state, India. In: Proceedings of Fifth International Conference on Soft Computing for Problem Solving: SocProS 2015, vol. 2, Springer, pp. 285–292.
Singh, T., Uppaluri, R., 2023. Machine learning tool-based prediction and forecasting of municipal solid waste generation rate: a case study in Guwahati, Assam, India. Int. J. Environ. Sci. Technol. 20 (11), 12207–12230.
Šomplák, R., Smejkalová, V., Roseckỳ, M., Szásziová, L., Nevrlỳ, V., Hrabec, D., Pavlas, M., 2023. Comprehensive review on waste generation modeling. Sustainability 15 (4), 3278.
Song, J., He, J., Zhen, J., 2015. Real-time data assimilation for improving linear municipal solid waste prediction model: A case study in seattle. J. Energy Eng. 141 (4), 05014002.
Srivastava, A., Jha, P.K., 2023. A multi-model forecasting approach for solid waste generation by integrating demographic and socioeconomic factors: a case study of Prayagraj, India. Environ. Monit. Assess. 195 (6), 768.
Stergiou, K., Ntakolia, C., Varytis, P., Koumoulos, E., Karlsson, P., Moustakidis, S., 2023. Enhancing property prediction and process optimization in building materials through machine learning: A review. Comput. Mater. Sci. 220, 112031.
Sun, N., Chungpaibulpatana, S., 2017. Development of an appropriate model for forecasting municipal solid waste generation in Bangkok. Energy Procedia 138, 907–912.
Suykens, J.A., Vandewalle, J., 2000. Recurrent least squares support vector machines. IEEE Trans. Circuits Syst. I 47 (7), 1109–1114.
Tan, J.M., Liao, H., Liu, W., Fan, C., Huang, J., Liu, Z., Yan, J., 2024. Hyperparameter optimization: Classics, acceleration, online, multi-objective, and tools. Math. Biosci. Eng. 21 (6), 6289–6335.
Tu, Y., Xiao, Z.X., Shen, N., 2022. Multivariate Analysis and Index Forecast of Influencing Factors of Shanghai Municipal Domestic Waste Generation. Technical Report, SAE Technical Paper.
United Nations Department of Economic and Social Affairs, 2025. SDG indicators database. https://unstats.un.org/sdgs/dataportal/database. (Accessed 11 February 2025).
Verdonck, T., Baesens, B., Óskarsdóttir, M., vanden Broucke, S., 2024. Special issue on feature engineering editorial. Mach. Learn. 113 (7), 3917–3928.
Vu, H.L., Ng, K.T.W., Richter, A., An, C., 2022. Analysis of input set characteristics and variances on k-fold cross validation for a recurrent neural network model on waste disposal rate estimation. J. Environ. Manag. 311, 114869.
Wan Ahmad, W.K.A., Ahmad, S., 2013. Arima model and exponential smoothing method: A comparison. In: AIP Conference Proceedings, vol. 1522, (1), American Institute of Physics, pp. 1312–1321.
Wang, G., Luo, X., Gu, R., Yang, S., Qu, Y., Zhai, S., Zhao, Q., Li, K., Zhang, S., 2023. PyMIC: A deep learning toolkit for annotation-efficient medical image segmentation. Comput. Methods Programs Biomed. 231, 107398.
Wang, K., Zhu, Y., Zhang, J., 2021. Decoupling economic development from municipal solid waste generation in China's cities: Assessment and prediction based on Tapio method and EKC models. Waste Manage. 133, 37–48.
Wei, N., Li, C., Peng, X., Zeng, F., Lu, X., 2019. Conventional models and artificial intelligence-based models for energy consumption forecasting: A review. J. Pet. Sci. Eng. 181, 106187.
Wen, Z., Shi, J., He, B., Chen, J., Ramamohanarao, K., Li, Q., 2019. Exploiting GPUs for efficient gradient boosting decision tree training. IEEE Trans. Parallel Distrib. Syst. 30 (12), 2706–2717.
Wikurendra, E.A., SYAIFUDDIN, A., Herdiani, N., Nurika, G., 2023. Forecast of waste generated and waste fleet using linear regression model.
Wilson, D.C., Rodic, L., Modak, P., Soos, R., Carpintero, A., Velis, K., Iyer, M., Simonett, O., 2015. Global Waste Management Outlook. Unep.
Wilts, H., Garcia, B.R., Garlito, R.G., Gómez, L.S., Prieto, E.G., 2021. Artificial intelligence in the sorting of municipal waste as an enabler of the circular economy. Resources 10 (4), 28.
Wu, F., Niu, D., Dai, S., Wu, B., 2020. New insights into regional differences of the predictions of municipal solid waste generation rates using artificial neural networks. Waste Manage. 107, 182–190.
Xia, W., Jiang, Y., Chen, X., Zhao, R., 2022. Application of machine learning algorithms in municipal solid waste management: A mini review. Waste Manag. Res. 40 (6), 609–624.
Xu, P., Ji, X., Li, M., Lu, W., 2023. Small data machine learning in materials science. Npj Comput. Mater. 9 (1), 42.
Xu, A., Li, R., Chang, H., Xu, Y., Li, X., Lin, G., Zhao, Y., 2022. Artificial neural network (ANN) modeling for the prediction of odor emission rates from landfill working surface. Waste Manage. 138, 158–171.
Yang, H.T., Chao, H.R., Cheng, Y.F., 2022. Forecasting and controlling of municipal solid waste (MSW) in the Kaohsiung city, Taiwan, by using system dynamics modeling. Biomass Convers. Biorefinery 1–9.
Yang, X., Wang, Y., Byrne, R., Schneider, G., Yang, S., 2019. Concepts of artificial intelligence for computer-assisted drug discovery. Chem. Rev. 119 (18), 10520–10594.
Yatim, F.E., Boumanchar, I., Srhir, B., Chhiti, Y., Jama, C., Alaoui, F.E.M., 2022. Waste-to-energy as a tool of circular economy: Prediction of higher heating value of biomass by artificial neural network (ANN) and multivariate linear regression (MLR). Waste Manage. 153, 293–303.
Younes, M.K., Nopiah, Z., Basri, N.A., Basri, H., Abushammala, M.F., Maulud, K., 2015. Prediction of municipal solid waste generation using nonlinear autoregressive network. Environ. Monit. Assess. 187, 1–10.
Yu, R., Leung, P., Bienfang, P., 2006. Predicting shrimp growth: artificial neural network versus nonlinear regression models. Aquac. Eng. 34 (1), 26–32.
Zanotti, C., Rotiroti, M., Sterlacchini, S., Cappellini, G., Fumagalli, L., Stefania, G.A., Nannucci, M.S., Leoni, B., Bonomi, T., 2019. Choosing between linear and nonlinear models and avoiding overfitting for short and long term groundwater level forecasting in a linear system. J. Hydrol. 578, 124015.
Zargar, S., 2021. Introduction to Sequence Learning Models: RNN, LSTM, GRU, vol. 27606, Department of Mechanical and Aerospace Engineering, North Carolina State University, Raleigh, North Carolina.
Zhang, Y., 2013. The prediction of the generation of municipal solid waste based on grey combination model. Adv. Mater. Res. 807, 1479–1482.
Zhao, Y., Li, H., 2023. Understanding municipal solid waste production and diversion factors utilizing deep-learning methods. Util. Policy 83, 101612.