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A Mini-Review for Identifying Future Directions in Modelling Heating Values for Sustainable Waste Management

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Keywords:	heating value, energy content, municipal solid waste, physiochemical analyses, AI-based modelling, circular economy

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Global estimations suggest energy content within municipal solid waste (MSW) is underutilized, compromising efforts to reduce fossil CO_2 emissions and missing the opportunities for pursuing circular economy in energy consumption. The energy content of the MSW, represented by heating values (HV), is a major determinant for the suitability of incinerating the waste for energy and managing waste flows. Literature reveals limitations in traditional statistical HV modelling approaches, which assume a linear and additive relationship between physiochemical properties of MSW samples and their HVs, as well as overlook the impact of non-combustible substances in MSW mixtures on energy harvest. AI-based models show promise but pose challenges in interpretation based on established combustion theories. From the variable selection perspectives, using MSW physical composition categories as explanatory variables neglects intra-category variations in energy contents while applying environmental or socio-economic factors emerges to address waste composition changes as society develops. The paper contributes by showing to professionals and modellers that leveraging AI technology and incorporating societal and environmental factors are meaningful directions for advancing heating value prediction in waste management. These approaches promise more precise evaluations of incinerating waste for energy and enhancing sustainable waste

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1. Introduction

Globally, the MSW management capacity has not kept pace with the increasing global annual municipal solid waste (MSW) generation (Kaza et al., 2018). Traditional MSW treatment methods like landfilling and dumping disturbed biogeochemical cycles (Canadell et al., 2021), leading to increased greenhouse gas emissions (Shang et al., 2019) and heavy metal-rich leachate (Khandelwal et al., 2019; Ma et al., 2018). The development of multiple energy-from-waste (EfW) technologies, such as incineration with energy recovery, pyrolysis, industrial co-combustion, gasification, and anaerobic digestion, makes MSW now a promising alternative energy source to fossil fuel. Assuming the average lower heating value (LHV) of 9 MJ/kg for MSW estimated by Scarlat et al. (2015), the annually recoverable energy potential of global MSW currently is 1.81×10^{19} J, equivalent to the energy produced from 430 Mt of crude oil (with an LHV of 42.3 MJ/kg). This avoids further releasing 1.33 Gt of CO_2 equivalent (CO_2-eq.) (estimated based on the parameters in IPCC, 2006; IPCC, 2019). Further, in the sixth assessment report by IPCC (Canadell et al, 2021), landfill has been identified as the major sources of fugitive CH_4, a more potent greenhouse gases (GHG) (GWP of 27-30 over 100 years); incinerating the excavated waste from the existing landfill is the mainstream solution to convert the emission (CH_4) that produce stronger warming effect to the weaker one (CO_2). However, World Bank estimated that less than 20% of MSW is recovered for its energy, and over 60% of MSW is disposed of in landfills (Kaza et al., 2018), implying unexploited sources of energy from MSW and unmitigated environmental impacts from the landfills. Habib et al (2013) and Tabata (2013) showed that with careful planning and implementation, incineration of MSW with heat and power recovery could turn the MSW management system into a carbon-negative system. Some cities, e.g., Stockholm, Sweden (Iveroth et al., 2013), and Kobe, Japan (Tabata, 2013), have achieved high-energy conversion efficiency from waste so that a noticeable part of household energy needs can be supplied completely from EfW facilities. Fossil related power generation and associated carbon emission are avoided.

As the carbon trading systems have now been established globally, economic gain from such emission reduction might have been anticipated. According to the carbon pricing dashboard established by the World Bank, current carbon prices announced by a variety of compliance mechanism range from US$0.07 (US$/tCO2eq) to US$155.86 (https://carbonpricingdashboard.worldbank.org/, as of May 09 2024). Meanwhile, the economic cost savings from reduced fossil fuel usage can fluctuate significantly (Vochozka et al, 2020). For example, the 52-week Brent Crude oil price as of May 09 2024 ranges from 71.50 - 95.96 USD per Barrel. The spatial-temporal variation in carbon and energy prices presents challenges in accurately estimating monetary costs and benefits. Therefore, this study primarily focuses on the climate benefits derived from actual carbon reductions.

However, based on the fluctuating range of Brent Crude oil prices during 2024, we can roughly estimate potential fossil energy savings in the range of several hundred billion US dollars when discussing the monetary benefit.

Among EfW technologies, incineration is favoured for its technical and socio-economic benefits (Shi et al., 2016; Kumar and Samadder, 2017), especially in dealing with the impacts left by landfill and dumping sites. By 2020, over 6,000 MSW incineration plants globally handled 74Mt of waste annually, mostly with energy recovery functions (Table S1). More incineration plants for energy recovery are expected to be commissioned in the years to come (World Energy, 2021). The design and operation of incineration EfW facilities are influenced and sometimes determined by the heating value (HV) of MSW which is either reported as a higher heating value (HHV) or LHV (Putna et al., 2014). HHV represents the amount of heat released when a unit weight of the compound is stoichiometrically burned completely, with all combustion products cooled to a standard state of 298.15 K (25°C) and 101,325 Pa (1 atm), and any water contained within the compound or produced during the oxidation is present in the liquid state (Meraz et al., 2003). LHV refers to the heat that can be harvested by the complete combustion of a specified quantity of fuel (initially at 25°C, 298.15K) without recovering the latent heat of vaporization of water formed during the reaction after the combustion products' temperature is then returned to 423.15K (150°C) (Bilgen et al., 2012). The ways to harvest the energy effectively from the waste with a specific range of HV affects the design of the key equipment (e.g., the length of the kiln), the application of supplementary fuel, and the maintenance and management of the facilities (Putna et al., 2014; Oumarou et al., 2018). Sending MSW with an unsuitable range of HV to incineration EfW facilities reduces the energy harvesting efficiency, curtails life span of the equipment or facilities, and produces undesirable pollutions (Putna et al., 2014; Xie et al., 2021). LHV of MSW, the amount of MSW incinerated and the vapour produced during incineration process greatly affected boiler efficiency; they influence the expected performance of a planned retrofit incineration plant as a EfW facility (Benácková et al., 2012; Directive 2008/98/EC, 2008, ANNEX II); only after understand the energy efficency of a designed energy recover operations in the incineration process, the cost effectiveness of the technology can be evaluated. As such, the LHV of MSW signifies its suitability for direct use as fuel. For example, food waste, usually with high water content, consumes the energy for evaporation during combustion resulting in lower LHV, implying much lower harvestable energy via incineration without pre-treatment such as dewatering. Overall, understanding MSW HVs aids in planning and managing waste material flow to close the loop of the system, maximizing energy and resource recovery efficiency (Tomic and Schneider, 2018).

HV of MSW samples can be directly measured in a lab using a calorimetric bomb, a type of calorimeter. The established relationship between HV and the chemical properties of substances has aid to estimating HV using empirical models based on measurable chemical properties of MSW and the knowledge of combustion (Khuriati et al., 2017). As regularly using calorimetric methods to measure HV of MSW *ad hoc* for an EfW facility is constrained by technical (Mateus et al., 2021) and financial requirements (Amen et al., 2021), obtaining estimated HV using predictive models are now feasible and preferred for its time- and cost-saving nature. However, imprecisions and variabilities in published models stem from several factors including failing to indicate the measurement basis (e.g., dry- or wet-basis) of the variables (Meraz et al., 2003; Nwankwo and Amah, 2016), failing to clarify the type of HV estimated (HHV or LHV) (Li et al., 2001), and lacking quality checking when the secondary data are used (Shi et al., 2016; Boumanchar et al., 2019). In considering MSW as potential sources of energy to reduce fossil fuel consumption, estimating its HV with higher precision may give better evaluation on how EfW technology contribute to carbon reduction.

Traditionally, the statistical techniques, mainly multiple regression analysis (MRA), are applied in building HV prediction models for MSW; the application of the artificial intelligence (AI) based approaches emerged in the literature since late 2000s (*e.g*. Shu et al, 2006; Ogwueleka and Ogwueleka 2010). The choice of the model building methods dictates the outcomes of the models and hence the applications.

The precision of HV estimation impact the design and operation of incineration EfW facilities and the management of waste material flows. Hence, the mini-review address the question regarding what factors influence the efficiency of extracting energy from MSW through incinerating using available level of technologies. We answer the question by examining the explanatory variables applied in existing HV prediction models for MSW as well as the mathematical methodologies applied in model construction. The explanatory variable in these models represent the current understanding of how a various factors influence HV of MSW and the directions of manipulating certain factors to enhance energy recovery efficiencies. The mathematical approaches employed in model construction influence the numerical interpretation of how those factors impact energy harvesting, thereby affecting the precision and accuracy of the HV estimation. Previous reviews addressing similar objectives lack comprehensive coverage in waste management and circular economy aspects. For instance, Vargas-Moreno et al. (2012) reviewed variables in HV prediction models for biomass, yet these models may not suitably estimate HV for the more complex and diverse composition of MSW (Ezzahra Yatim et al., 2022). This earlier review did not cover AI as a model-building techniques for HV. Adeleke et al. (2021) reviewed the HV prediction models specifically for energy recovering potential for the MSW in developing countries. Dashti et al. (2021) reviewed the HHV prediction models for MSW regarding how such model can be developed using AI-based approaches without comparing it to the traditional statistical approaches.

To comprehensively answer the question of interest, this systematic literature review (Methodological framework is in Appendix S2) is conducted in the following steps: (1) critically examines the published models predicting the HV of MSW based on the knowledge of how factors affect the energy released during the MSW combustion (Section 2); (2) evaluate the methods measuring the physiochemical compositions of MSW (Section 2) as the foundation for HV prediction; (3) assess the performance of the numerical techniques employed to construct HV prediction models (Section 3); and (4) identify possible omissions, errors and imprecisions in model development (Sections 2 and 3). In Section 4, a synthesized discussion will explore how modelling techniques and waste generation trends shape future waste management and circular economy perspectives, leading to conclusions in Section 5.

2. Models for predicting HV of MSW

Without being measured using a calorimetric bomb every time, the HVs of MSW can now be estimated based on the measured chemical-physical properties of MSW using established models. The environmental (Siddiqui et al., 2017; Birgen et al., 2021) and socio-economic factors (Putna et al., 2014; Das et al., 2019) influence the patterns of consumption and thus the types and properties of the generated waste (Wang et al., 2018; Baghban and Ebadi, 2019).

Reviewed studies predominantly established HV prediction models based on physicochemical properties of MSW. Occasionally, these models incorporated selected environmental and/or socio-economic factors (see Fig. 1). Studies estimating HV using the same physiochemical properties identified varied patterns among municipalities with low, medium, and high income levels (e.g., Ozcan et al., 2016; Amen et al., 2021; Mondal and Kitawaki, 2023). Integrating indirect socio-economic and environmental parameters in HV prediction models is expected to enable projections of the HV during the transition of the societies and environmental changes based on the forecasted seasonable variations and potential changes of MSW compositions (Putna et al., 2014).

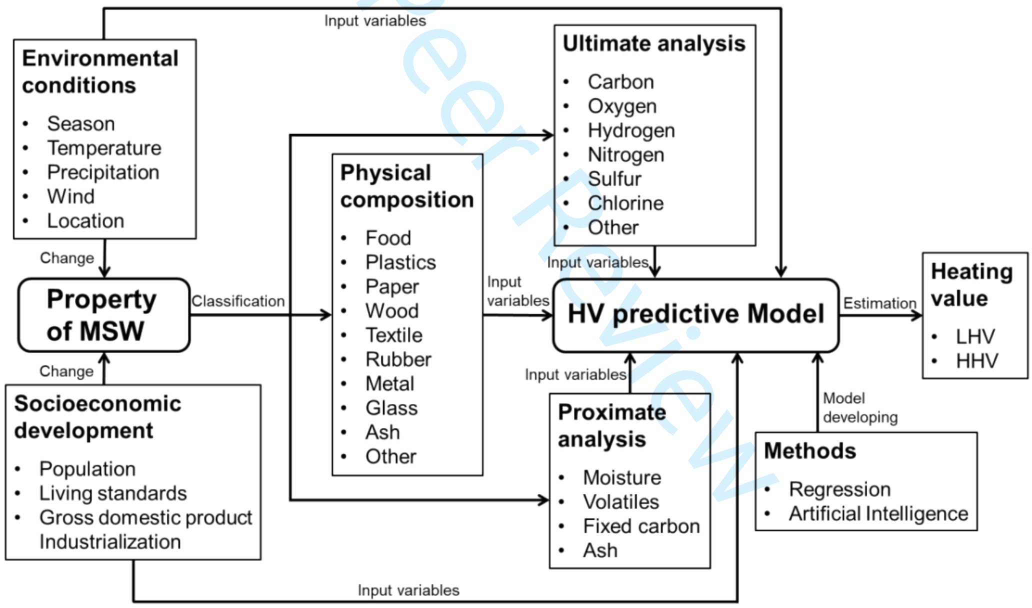

Fig. 1. The interrelationship between chemical-physical properties of MSE, external factors and numerical approaches for modelling HV for MSW (adapted from Birgen et al. (2021)).

Three conventional sets of chemical-physical characteristics of MSW have been measured for estimating its HV: ultimate analysis identifies the elemental components of MSW samples in weight percentage (wt. %) (Baawain et al., 2017), proximate analysis assess the proportions of materials burning in different states (volatile matter - VM, fixed carbon - FC, inorganic waste material - ash, and moisture - M) (Özyuğuran and Yaman, 2017; Nunes et al., 2018a), and analysis of physical composition measures the proportions of material categories (e.g., food, plastics, paper and textile) in MSW. The rationales of using these three types of measurement are rooted in the scientific understanding of how specific physical and chemical properties of the MSW to be incinerated directly impact the energy recovery from MSW. We compared and contrasted the feasibilities and precisions of the models derived using the three approaches in the literatures (Appendix S3) hereby.

2.1. Models based on ultimate analysis

Ultimate analysis determines the elemental composition, often focusing on carbon (C), hydrogen (H), oxygen (O), nitrogen (N), and sulphur (S), in samples. HV prediction models based on the results of ultimate analysis were originally developed for evaluating energy contents in coal as a fuel. Thus, content of C is considered essential while other elements may be optional. Since the millennium, the numbers of models established using the results of ultimate analyses on MSW are increasing (Table S2). In these models, C, H, and O contents are the often-used explanatory variables. For the MSW with high content of organic matter, S and N are added. Sometimes, chlorine (Cl), moisture content and ash are included (Akkaya and Demir, 2009; Eboh et al., 2016). Elements selected to be analysed may not always be included in the final models; this happens when the amounts of the elements are untraceable in the ultimate analyses, or the contributions of the elements to HV are negligible in the output of the modelling. Thus, the models built in this way could be case-specific and could not be applied with confidence to other cases. Provided the MSW compositions vary, the contributions of the excluded elements to the HV require re-evaluation. Likewise, the simplified models including only carbon and/or hydrogen (Khuriati et al., 2017; Boumanchar et al., 2019) usually show acceptable performance in the original research but cannot be generalized or extrapolated for predicting HV of the MSW outside that specific research.

Some general trends regarding how elements contributed to the heating value can be observed among these models: C, H, and S in MSW positively contribute to the HV; the oxidation of these elements is usually exothermic (Cooper et al., 1999). Unexpected negative contributions of these elements in specific cases may result from unique MSW compositions (e.g., high proportions of nylon or organic waste) or technical modeling issues like collinearity (Ibikunle et al., 2018; Eboh et al., 2016). Additionally, the positive contribution of these exothermic elements to HV might be counteracted by other physiochemical properties, such as uneven ignition of textile materials (Nunes et al., 2018b). In most models, HVs are negatively correlated with O content, but the contributions of O become positive to HVs when that of H is negative (Meraz et al., 2003; Kathiravale et al., 2003). The forms O and H exist in materials impact the combustion process. For example, hydrated chemicals increases the contents of H in MSW composition, and removing water from the hydrated chemicals consums more energy than evaporate free water (Zhou et al., 2008). Hence, H exist in such compounds could contribute negatively to the harvestable energy in MSW. Studies sometimes indirectly estimate O content in MSW (Boumanchar et al., 2019) tend to overestimate O content and hence underestimated its its potential correlation strength (if significant) with HV.

Overall, the model established based on ultimate analyses exhibit precision in predicting HV, yet this method relies on costly elemental analysers and entails time-consuming, and technically demanding procedures (Shu et al., 2006; Table 1). The small sample unit (mg) used in analysis poses issues concerning the representativeness of the overall MSW content, usually measured in tons (Table 1). In addition, these models may have overlooked the factors beyond the elemental composition involved in energy releasing during the combustion. The previous example of H and O illustrates the element can exist either as part of energy generating compounds or energy consuming compounds during combustion.

Table 1. Procedural characteristics of the physical chemical analyses and the theoretical base for their applications in HV prediction

	Ultimate analysis	Proximate analysis	Physical composition analysis
Time required for analysis (Shu et al., 2006)	4–5 days	4–5 days	1–2 days for wet-base; 2–3 days for dry-base
Skill and material requirements	High	Medium	Low
Size of samples (Kathiravale et al., 2003)	1–10 mg	1–5 g	50–100 kg
Sample representativeness	Low	Medium	High
The theoretical base for the estimation	The summation of the heat released after major elements (C, H, O, N, S, and Cl) in the organic compounds are completely oxidized represents the heat released from combustion. Thus, the percentage of the elements in the organic compounds can be used for predicting the heat of combustion of the compounds. The earliest and symbolic estimation equation is Dulong's Formula (Wilson, 1972).	The energy released via carbon-rich organic matter (e.g., coal or biomass) through combustion can be estimated primarily based on its carbon content, with the adjustment of the contents of volatile matter, and ash. The moisture content was originally used for weight adjustment in estimating HHV based on the dry weight of the substance, not treated as a variable in the estimation (Channiwala and Parikh, 2002; Özyuğuran and Yaman, 2017). It may be included when LHV is	A good consistency was obtained between the higher heating values (HHV) estimated using the physical compositions of MSW and the modified Dulong equation based on the elemental composition of the same set of data. Thus, it is suggested that the physical composition of MSW can large-partly represent the chemical composition to be used in estimating the HV (Khan and Abu-Ghararah, 1991).

		estimated considering the effect of latent heat.	
Size of the settlements where waste management operation covers (Shu et al., 2006)	Cities	Cities	Villages, towns, cities
Development status of operating agents	Economically developed	Economically developed	Economically developed and economically emerging
Applicability to phase in the life cycle of an incinerator	Design stage	Design stage	Design stage, operational stage
Estimating LHV or HHV	Mostly HHV	Mostly HHV	Mostly LHV
Modelling methods	Linear regression, non-linear regression, AI approaches	Linear regression, non-linear regression	Linear regression, non-linear regression, AI approaches
Model accuracy	High	Low	Medium
General linear pattern of the model	$HV = aC + bH + cO + dN + eS + fCl$ + g	$HV = aVM + bFC + cA + dM + e$	$HV = aFo + bPl + cPa + dTe + eWo + fRu + gM + h$
Globally applied model	None	None	None

C, H, O, N, S and Cl are the percentage of carbon, hydrogen, oxygen, nitrogen, sulphur and chlorine by weight, respectively; VM is the percentage of volatile matter; FC is the percentage of fixed carbon; A is the percentage of ash; M is moisture content; *Fo* is the percentage of food waste by weight; *Pa* is the percentage of paper and cardboard waste by weight; *Pl* is the percentage of plastics waste by weight; *Te* is the percentage of textile waste by weight; *Wo* is the percentage of wood waste by weight; Ru is the percentage of rubber and leather; lowercase letters a–h are the coefficient of variables and constant.

2.2. Models based on proximate analysis

Proximate analysis, used for over 160 years as a less expensive and easier-to-operate alternative to ultimate analysis for coal rank measurements, has primarily used for estimating the HV of coal and biomass (Akkaya, 2013; Tan et al., 2015; Samadi et al., 2021; Dashti et al., 2019) and occasionally for MSW (Table S3). However, proximate analysis has been reported unsuitable in predicting the contribution of diverse macerals in the lower rank coal to the energy generation (Suárez-Ruiz and Ward, 2008). Possibly for same reason, models based on proximate analysis often exhibit poorer performance compared to those using ultimate analysis, resulting in less frequent use of proximate analysis for building HV prediction models for MSW.

In models derived from proximate analysis, HV generally correlates positively with FC and VM, while displaying a negative relationship with ash (A) and moisture content (M) in most cases (Table S3). However, as the volatile species are not always combustible (Özyuğuran and Yaman, 2017), VM was sometimes found to have an insignificant influence on the HV of MSW (Siddiqui et al. 2017). The variation in estimating the contribution of FC to the HV may result from the indirect measurement by deducting the measured contents of VM, M, and A from the total content (Basu, 2018), similar to the oxygen element in the ultimate analysis (section 2.1), which potentially increase the imprecision of HV estimation. Further, the collinearity between variables obtained from proximate analysis violates regression analysis assumptions and thereby affect model accuracy (Vargas-Moreno et al., 2012). Moreover, energy required for ash forming, thermal breakdown, and inorganic phase transition during combustion may not always be proportional to ash content (Özyuğuran and Yaman, 2017);

regression models, assuming linearity, may fail to properly capture this non-linear relationship (Amen et al., 2021). Despite the limited performance of proximate analysis, the inclusion of ash content in the model recognized the influence of some non-combustible elements, in addition to water, to the extractable energy from wastes.

2.3. Models based on the physical composition

Physical composition analysis is an expedient and less costly method tailored for estimating MSW's HV. Unlike the skill-intensive physiochemical measurements of ultimate or proximate analyses, analysing MSW's physical compositions is faster and cheaper (Table 1). Consequently, HV prediction models based on physical composition have gained traction in EfW facility practices (Drudi et al., 2019). Recent advancements in image recognition technology have further enhanced the real-time prediction of HV using physical components (Xie et al., 2021).

The HV prediction models established based on physical composition of MSW primarily rely on the percentages of combustible materials like paper, plastics, food, wood, rubber, and textiles (Appendix S3), while often overlooking proportions of incombustible materials like metal and glass (Oumarou et al., 2016). Some simplified models may only include food, paper, and plastics as predictors, given that these three categories typically constitute over 70% of MSW contents (Drudi et al., 2019; Wang et al., 2021); the streamlined models imply less effort in sorting physical composition in MSW samples.

The models based on MSW composition predict HV well in a case-specific manner, generalizing the numerical relationships can be problematic (Wang et al., 2021). Waste materials falling into the same categories exhibited variable HVs across regions and countries, leading to distinct regional features in the models. For example, the proportion of fat, protein and carbohydrates in the food waste reflect local lifestyles; as a result, the HV of food waste varied among places (Campuzano and González-Martínez, 2016). Besides, these models typically focus overlook the potential impact of inert substances mixed within the waste on combustion efficiency, compromising the precision in estimating HV (Özyuğuran and Yaman, 2017).

The physical composition-based models can inform a more effective way to manage the material flows such as separating and diverting the categories of waste with higher added value if recycled or with lower energy contents from incineration for energy recovery. In this way, sustainable waste management and the circular economy can be practiced. For example, the HHV of plastics ranges between 15.88–47.06 MJ/kg (Zhou et al., 2014; Shi et al., 2016). Recycling plastics with high HVs, such as polyethylene (HHV around 46 MJ/kg) lowers the average HV of remaining plastic mixture subjected for EfW (Calabrò, 2010). The extent to which the HV is reduced because of the recycling can be estimated for determining the amount of the recoverable energy that is reduced. This estimation allows managers to evaluate the economic viability of energy recovery versus material recovery from polyethylene in a site-specific manner.

2.4. Models based on other variables

Further to the models mentioned above, some unconventional variables such as the structural composition of MSW (Calabrò, 2010; Li et al., 2017), and environmental and socio-economic factors (Birgen et al., 2021) were used to predict the HV of MSW in literature. These models exhibited a reasonable explanatory ability for HV variations as indicated by the coefficient of multiple determination (R^2). The selections of these explanatory variables, though not directly related to the theories of combustion, make sense under the specific scenarios under which the waste management approaches need to be developed. In detail, Calabrò (2010) proposed a linear regression model to estimate the LHV of residual MSW based on the wet weights of cellulosic materials, polymeric materials, and water content present in 1kg of humid waste. Siddiqui et al. (2017) proposed two LHV prediction models and two HHV prediction models specifically for the use of disposed MSW in dumpsites based on the depth, bulk density, moisture content, and pH of landfilled MSW. As harvesting energy resources from dumped or landfilled materials becomes an increasingly prevalent solution of sustainable waste management, this type of models can be quite practical. Yet, a good application of these models can only be possible with the verified physiochemical properties of the landfilled MSW, and the site-specific conditions of the landfills. Birgen et al. (2021) proposed a well-performed AI-based model for daily LHV prediction of MSW using weather (temperature, wind stength and precipitation) and calendar (day of the week and week of the year) information. This type of models is useful in planning the waste management process and the design and operation of incinerators considering the changing HV of MSW resulted from the development of society and changing climate during the life span of incinerators (Oumarou et al., 2018).

3. Techniques to build HV prediction model of MSW

To estimate the HV of the MSW, the explanatory variables need to be mathematically linked to the HV of the same set of MSW measured using calorimetric bomb in the lab. The reviewed studies show that the link was made either by statistical or AI-based modelling. The assumptions and mathematical techniques employed in these two approaches differ, leading to distinct characteristics in the derived models. As a result, the interpretation and application of these models in waste management, such as designing and operating the incineration EfW facilities, may vary. This section reviews the two modelling techniques, analysing their strengths and weaknesses in predicting HV.

3.1. Multiple regression analysis (MRA)

MRA, a statistical method to determine the relationship between a dependent variable and one or multiple independent (explanatory) variables (Boumanchar et al., 2019), is a popular modelling method for developing HV prediction models (Appendix S3). The regression models are presented in the form of confirmed equations that describe the mathematical estimation of HV (dependent variable) based on statistically verified selected characteristics (Table 2). The equation can usually be interpreted based on the knowledge of the selected MSW characteristics (reviewed in section 2) and the combustion process. The strength and significance of the explanatory variables to the HV prediction can be verified with some commonly agreed evaluation criteria (e.g. the 95% confidence interval of explanatory and dependent variables as well as significance level of the coefficients and models) (Wang and Elhag, 2007).

Table 2. The characteristics of the two techniques to develop HV prediction models.

	MRA	AI-based approach
HHV or LHV (Appendix S3)	Both	Both
Model types	Mainly linear	Non-linear
Interpretation	Relatively straightforward based on the statistical significances and the coefficients of the explanatory variables in the regression equation.	There is no fixed equations or mathematical relationship provided. Thus, it is challenging to interpret the results based on the correlation between the input and output.
Confidence interval for prediction	Yes	No
Programming skill	No (not essential)	Yes
Model building based on specified assumptions or scientific theories	Yes	No
Inclusive/exclusive	Exclusive: the model was built by eliminating the independent variables that are statistically non-influential to the variability of dependent variables.	Inclusive: the model was built by including all the possible independent variables collected.
Applicability (interpretation based on the available theories)	Numerically feasible but theoretically problematic	Difficult

The number of explanatory variables in MAR-based HV prediction models is limited to allow a reasonable degree of freedom as the explanatory power of the model (Table 2) (Eftekhar et al., 2005; Nwankwo and Amah, 2016). The procedure of MRA promote model simplification by removing statistically insignificant variables to prevent type I errors (*i.e.,* the mistakes of including the insignificant variables, a threshold of an acceptable probability of making such mistake, the p-values, is usually set to be lower than 5%). As a result, the detailed properties of varied materials composed of MSW may not all be put into the MRA-based models. Besides, as reviewed in section 2, models established based on MSW physiochemical characteristics, environmental factors, or socio-economic conditions are case-specific; thus, when new datasets are included in the database for model building, different numerical relationships usually emerge (Eftekhar et al., 2005). Such models are safer to be used in predicting HV for the MSW compositions/contexts that closely resemble those from which they were estimated. Given the spatiotemporal variation of MSW properties and the continuous emergence of new materials in MSW (Das et al., 2019; Siddiqui et al., 2017), the MRA-derived models need regular update to adapt to the changing context. Furthermore, the physiochemical properties of MSW are unavoidably related to each other (Ibikunle et al., 2018); the potential multicollinearity between the independent variables in a model can violate the fundamental assumption of regression analysis; the resultant statistical model could be misleading. Eliminating one of the two highly correlated explanatory variables, both theoretically contributed to the HV, offers a numerical solution. However, it may compromise model precision and limit its application.

3.2. AI-based techniques

AI refers to a technique associated with constructing a machine or a completely computerized and coded instrument that performs tasks in ways human would do intellectually (Fetzer, 2012). AI-based techniques can extract the information in the training data that are not discernible by traditional statistical methods (Wang et al., 2021). They handle multiple types of inputs and an unlimited number of explanatory variables (in theory).

AI-based approaches, similar to the idea of grounded theory, is assumption free, unlike statistical approaches (Eftekhar et al., 2005). In the past decades, AI-based methods, including artificial neural network (ANN), genetic algorithms (GA), adaptive neuro-fuzzy inference system (ANFIS), support vector machine (SVM), etc. (Abdallah et al. 2020, Appendix S3), have shown excellent performances in estimating the HV of MSW. From the literature reviewed, ANN is slightly more popular (Appendix S3) techniques (Dong et al., 2003; Khuriati et al., 2015). The precision of AI generated models was evaluated using established indicators such as mean square error, mean absolute percentage error, etc. (Gong et al., 2017; Rostami and Baghban, 2018).

Several barriers hinder the full adoption of AI techniques in building the HV prediction model. These include the unexplainable behaviour of the network, the difficulty in determination of proper network structure, and the unknown duration of the network (Tu, 1996; Mijwel, 2021). AI modelling also demands more computational resources than MRA does. The assumption-free characteristics make the working procedure like a black box; as a result, it is challenging to validate the AI-based model at the individual variable levels based on the knowledge of the chemical mechanisms involved in incineration process (Eftekhar et al., 2005; Wang et al., 2021) or the socio-economic developlemt affecting the waste generation. The ambiguity in the process of determining the structure of running AI models (Eftekhar et al., 2005) and the need of experiences for trial and error to find the best-fit model structure (Mijwel, 2021) make the experience of the programmer equally important as the selection of AI-based approach. Applying the same AI-based method to analysing the same dataset in separated trials may produce models with different structures, while the same regression method and procedure combined with the same set of data derive reproducible results. Yet, the past 2 years or so seen the application of AI techniques in predicting HV catching up with the traditional statistical technology (Appendix S3). The popularity of AI techniques in various aspects of MSW management has been increasing (Lin et al., 2022; Fang et al., 2023).

Partly, the AI-based model, given sufficient computation power, is versatile; it is forgiven for the data quality, yet requires a larger amount of data points. AI modelling appears to be more robust in finding the best fit for the relationship between multiple socio-economic factors and environmental or material characteristics. Socio-economic and environmental factors are now recognized as useful explanatory variables for predicting HV (section 2.4), their implicit relationships with waste types and compositions may be better captured by AI-based models that embrace flexible and non-linear relationship. This capability to identify non-linear patterns may also accommodate the influences of non-combustible ingredients mixed in the waste to be incinerated. For example, the AI-based models derived from proximate methods may perform better when non-linear influences of ashes are accounted for (Dodo et al, 2024). On the other hand, this may lead to a more case-specific model, reducing likelihood of general interpretation.

3.3. Comparison between MRA and AI-based model on performance

Looking at R^2 values of HV prediction models, a versatile indicator for model performance, we found that increasing number of explanatory variables in a model does not improve the performance (Fig. 2). Specifically, the AI-derived models mostly exhibited R^2 higher than 0.8 regardless of the number of variables, while the MRA-based models showed R^2 at a bigger range (between 1 and 0.5). It is unclear whether the higher R^2 values for AI generated models are sometimes the result of over-fitting. Lin et al. (2022) pointed out that overfitting often happened for AI-based models, especially the ones built using neural network approaches. With known statistical procedure, on the other hand, is it certain that lower R^2 of an MRA-based model implies that not all explanatory variables that can explain the variation of HV are included in the model.

Increased sample size did not improve R^2 values either. Small sample size could lead to over-fitting easily for not only AI-derived models but sometimes MRA-based models. Models generated using bigger sample size, on the other hand, may exhibit slightly smaller R^2, revealing a more realistic internal variability inherited in samples, especially for the MRA-based modelling. Interestingly, in the literature we reviewed, the sample size for AI-based models or MRA modelling exceed 250 only occasionally (Appendix S3) while the sizes of datasets used for building HV prediction models for MSW via ANN seldom surpass 500. However, Nghiep and Al (2001) indicated that only when the dataset size exceeded 506, the models built using ANN started to outperform MRA. Considering the sample size in a regression model usually far exceed the number of explanatory variables, from this aspect, the MRA models published for HV prediction usually can provide sufficient statistical power. Exploring how to establish and acquire larger size of datasets (e.g., over 500) become a key for improving the suitability of AI-based approaches in building an HV prediction model (Abdallah et al. 2020).

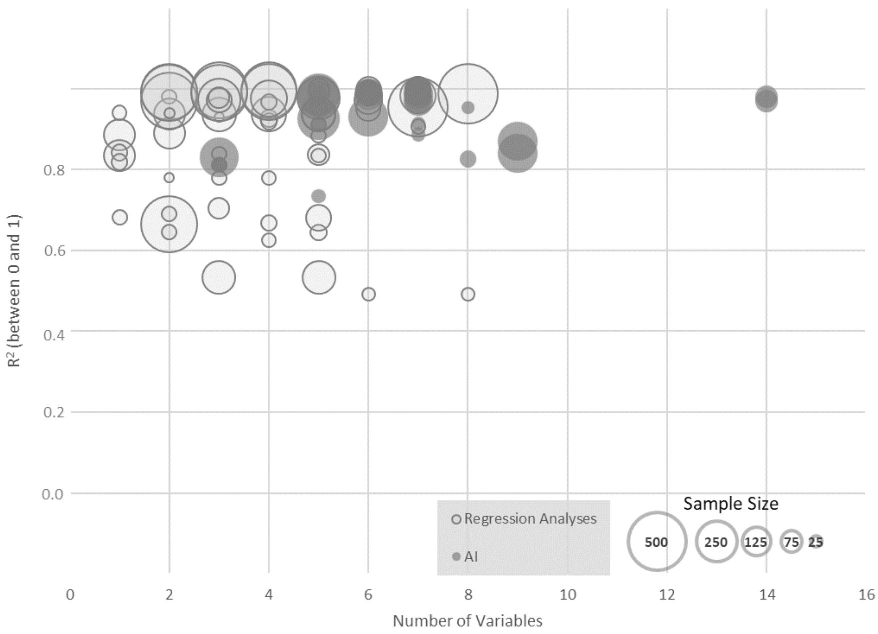

Fig. 2. The relationship between model performance (R^2), the number of explanatory variables, and sample size reported in the literature.

4. Discussions

This review systemically evaluated the construction of HV prediction models incorporating the factors affecting the HV of MSW based either on the theories of combustion, or on changing environment and lifestyles. Technically, accurately estimated HV inform effective planning in selecting, designing, and operating EfW facilities. From a broader perspective, understanding the factors influencing energy content (represented by HV) in the MSW aids holistic waste management practice. For instance, to reduce the landfill rates, countries may increase the recycling rates or convert the waste for energy considering cost-benefit or technological feasibility (Wang et al., 2022). The knowledge of the projected waste composition and the energy content shapes cost-benefit evaluation and technology selection (Bergeron, 2017). Based on the review in section 2 and 3, therefore, this section critically evaluates challenges observed in the HV prediction that should be overcome to further enhance the usefulness of models in developing and implementing EfW technologies, supporting sustainable MSW management for circular economy.

4.1. Reporting moisture content for waste management

The cases documented in the literature reported the modelling or experimental results either in the form of HHV or LHV (Chang et al., 2007) while the relationship between HHV and LHV of waste can be described numerically (see formulas in Appendix S4). From the perspective of energy recovery, LHV reflects more realistically the available energy to be converted into heat or electricity through incineration (Oumarou et al., 2018) by discounting the latent heat the water in MSW consumes for evaporation, the unattainable portion of energy during combustion (Pavlas et al., 2011). From an engineering and technical point of view, LHV provides the base to estimate the amount of energy that maintains or increases the temperature in the combustion chamber. The net energy released from burning MSW dictates the minimum internal volume required for the chamber and influences the need for auxiliary fuel or pre-treatment during the operation stage (Oumarou et al., 2018).

Moisture affects the latent heat and the weight percentage of MSW composition. Thus, both HHV and LHV vary depending on the moisture content in MSW (Boumanchar et al., 2017). To be clear and consistant, most of the relevant literature reviewed reported HV expressed on a dry basis (MSW). However, this reporting cannot be useful in evaluating pre-treatment or the addition of the auxiliary fuel which may maximize the energy recovery, sustain the combustion, or reduce the pollutant emission. As such, reporting HV on a wet basis may have practical values (Siddiqui et al., 2017). The chllenges for this is that moisture content is changeable: moisture in MSW reduces by 9–15 % after five days of storage (Tumuluru et al., 2021), which increases the LHV by 1500–3000 kJ/kg (Lu et al., 2017). To address this issue, some studies reported HV at "as received" (Nzioka et al., 2019). Reporting the LHV of MSW together with its moisture content may be necessary to better inform the operators to what extent the pre-treatment is required.

Some models we reviewed treat the moisture content as the explanatory variable for estimating either HHV or LHV. Especially, the models utilized the physical compositions of MSW as explanatory variables started incorporating the moisture content as early as 1996 (e.g. Liu et al. 1996). The moisture content is the primary variables in the proximate analysis. Yet, the moisture content appears in the models based on ultimate analysis only after 2020 (e.g. Amen et al, 2021); possibly, previously, it was considered that the contents of O and H detected by the ultimate analysis in the models are sufficient to represent the effect of water. However, as discussed previously, the H and O exist also in other compounds that affect heating values in different ways; practically, moisture content may be influential enough to be considered as another significant explanatory variable. Moisture content appears in AI-based models quite frequently and as early as when the type of approach has just emerged at the beginning of the Millennium.

The trend observed in literatures showed that moisture content has been recognize as an influential factor for the decision-making of recovery energy from the MSW using direct incineration or other recovery methods such as anaerobic digestion or making refused derived fuel (Dong et al., 2016; Hasan et al., 2021).

4.2. Selection of linear or non-linear model

Traditional mathematic methods (e.g., regression) describe a linear relationship between explanatory variables and HV in a model (Appendix S3). Yet, nonlinear mathematical models established using the same set of data may show competitive accuracy (e.g. Nwankwo and Amah, 2016; Boumanchar et al., 2019). Wang et al. (2021) showed nonlinear but positive correlation between percentages of each combustible physical compositions in MSW and LHV. These observations may partly result from the internal variabilities of MSW within the same categories, discussed in previous sections, and partly result from discounting the influences of inert substances within those physical composition. At an elemental and molecular level, Patel et al. (2007) illustrated that the relationship between HHV and S content, N content or moisture content can be non-linear. Amen et al. (2021) observed the nonlinear relationship between the components in proximate analysis (ash, volatile materials, fixed carbon, and moisture) and HHV, as well as the elemental composition (C, H, N, O, and S) and HHV. These studies demonstrated that estimating HV involves more than simply summing up the energy theoretically would be released during the oxidation of individual chemical elements or physical compositions.

Moreover, the presence of incombustible materials, such as metal and glass, may affect oxidation reactions during the combustion (Siriwardane et al., 2010), impacting the heat released and harvested. The work of some researcher who include the content of incombustible materials in their HV prediction models (Shu et al., 2006; Oumarou et al., 2016) showed overlooking the effects of these incombustible materials will mathematically distort the theoretical linear relationships between the combustible MSW compositions and the HV of the MSW into a non-linear relationship.

The developments of economy, technology, and living standards increased the complexity of MSW. This is expected to continue, and it is possible that the linear relationship between physiochemical properties of relatively few simple types of MSW no longer dominant during the combustion process happening in the incinerator. For example, the recent waste statistics have identified diapers as a new category of the waste (IPCC, 2019). Introducing new categories into the MRA-derived HV prediction model as explanatory variables could elevate the complexity of the model (provided all variables remain statistically significant). This may lead to reduced significance and influence of each category on HV. In some cases, the increased categories might render very few compositions influential enough to be retained in the model (Table 2) (Eftekhar et al., 2005). Unless waste sent for incinerating become more strictly selective, a HV prediction model that is more inclusive in terms of variables and non-linearity to the becomes more useful for decision making in directing waste material flows for proper treatment that may facilitate circular economy. In this aspect, AI-based approaches for their ability to accommodate the non-linearity and numbers of input variables show great potential. However, the size of dataset may affect the accuracy of the AI-based model considerably (section 3.3).

Our preliminary evaluation seems to show the data size and number of variables affected performance of the model generated using AI or MRA quite differently (Fig. 2). Yet, this is based on the cases in the literature available for review and may not cover all the relationships under a variety of scenarios (Dashti et al., 2021; Wang et al., 2021). Hence, further studies on the optimized numbers of variables and dataset size in building AI-based HV prediction models may be required to reduce the uncertainty and improve forecasting accuracy.

4.3. Managing uncertain and variable data

The high heterogeneity and spatiotemporal variation of MSW composition (Das et al., 2019) makes collecting representative data to model HV with higher precision challenging. Given that the municipality budget is limited, waste management needs to compete with other development priorities for the monetary resource. As a result, 33% of the world's MSW are not managed in an environmentally safe manner (Kaza et al., 2018); under this context, regularly measuring the physiochemical properties of MSW for evaluating potential EfW application is constrained.

As such, the use of publicly accessible secondary data is the second-best but necessary choice for modelling the HV of MSW (Ozveren, 2016; Baghban and Shamshirband, 2022). Yet, as the secondary data have been measured and collected using various methods and for different purposes, not specifically for HV estimation, reconciling inconsistency in data become critical. Wang et al. (2021) demonstrated that the performance of the LHV prediction models for MSW based on the compiled secondary data (LHVs and the corresponding physical composition of MSW) are acceptable but not as good as those built based on first-hand data, of which the variability in MSW composition is reported and can be accounted for.

Other uncertainties associated with MSW data are measurement bases and applied sampling standards. As described in section 4.1, HV measured on a dry or wet basis can return significantly different results. The choice of which type to reference and thus the prediction models to be used in designing EfW facilities may depend on the corresponding MSW collection and pre-treatment plan. Varied sampling and analysis standards lead to inconsistencies in HV measurement and reporting; thus, merging datasets to increase sample size for modelling may not always produce good results, which can significantly affect decision-making in waste management. Moreover, different sampling strategies affected the comparability between published models. Some literature refers to ASTM or Chinese national standards (CJ/T 313–2009 and CJ/T 96–2013) for waste sampling and analysis if not developing their own study methods. For the studies specify the standard followed, at least a proper comparison across a variety of models with reasonable adjustment may be possible.

Overall, the decisions on selecting energy recovery based or recycling based waste management strategies to facilitate the circular economy may rely partly on the knowledge of energy content of MSW. However, the uncertainties originated from data sources, sampling, analysing, and modelling make the HV prediction not as straightforward as it seems. Reducing uncertainty in any of these areas may help improve the quality of waste management decision making.

4.4. Application of models in MSW management

In practice, moisture evaporation consumes a vast amount of heat during 2/3 of the MSW combustion time (Sun et al., 2015). In models based on a wet basis of MSW, materials with high water content, for example food waste, contribute negatively to HV; likewise, moisture content contributes to HV negatively on a dry basis of MSW (Appendix S3). This general trend observed in the model demonstrated the importance and necessity of separating moisture-rich waste from the waste to be incinerated for better the energy recovery efficiency. By contrast, assessing the feasibility of energy recovery from specific MSW mixtures in certain locations or seasons through incineration could involve HV prediction models incorporating moisture content as explanatory variables (Birgen et al., 2021). Together with the knowledge of physical and/or chemical proportions of MSW, the simulation results of HV provides direction for the design and optimization of the incinerator, e.g., the length of combustion chambers, the application of drying or auxiliary fuel, and the waste collection strategies (Amen et al., 2021). The results of the modelling can also be a good reference to highlight the importance and benefits in harvesting energy through incineration from collected waste under desirable conditions (e.g. lower moisture content and less inert materials).

MSW is a mixture of materials distinct in chemical and physical properties. To extract energy or resources from such mixture effectively, in addition to sorting at the points of the collection, an integrated waste management system involving pre-treatments such as mechanical treatments and mechanical biological treatments is usually required (Amen et al., 2021). The procedures can separate the mixtures into sub-categories from which the resources can be extracted more effectively. In this aspect, data on the physiochemical properties of MSW (obtained from ultimate, proximate, or physical composition methods) can support the establishment or improvement of an MSW management system. In particular, HV derived from a variety of MSW mixture with different physiochemical properties under scenarios of MSW generations may aid decision-making in designing the integrated management system that optimizes resource utilization and reduce environmental impacts (Dashti et al., 2021). For example, LHV prediction model was used in the life cycle assessment of the MSW management in Nottingham from the perspective of low-carbon MSW management to further reduce the carbon emission (Wang et al., 2022).

4.5. On Circular Economy

Avoiding further exploiting fossil-based fuel is pivotal for sustainable development; as shown in the introduction, MSW holding substantial potential as a renewable energy source. This also convert the originally costly waste management process into a potentially profit making, or at least cost-reduction process for a municipality. Incineration for energy directly harnesses energy from waste without further processing, making it a preferable method if the received waste exhibits a sufficiently high HV; any additional processing to boost the energy content of end-product such as pyrolysis, consumes energy (e.g., Hasan et al, 2021) and cost money (Maroušek et al. 2023). They may not reduce the impurity (non-carbon elements) which produce undesirable pollutants during oxidation processes (Mardoyan and Braun, 2015). Therefore, evaluating the original heat content in the form of HV is important for selecting the cost-effectiveness EfW technologies. It is acknowledged that sometimes, the thermal conversion process produced not only fuel for energy but valuable end products, such as composts from biogas treatment plants (Bencoova, 2021). The HV evaluation may not be useful in evaluating such added value. However, the technical contents in the technologies as well as the requirement of the quality of inputting waste materials (for example, plants residuals from food production or food waste with high organic contents or specific portion of compositions) may allow the implementation of such technology to be in the areas the relevant industrial clusters located or where the waste collection and sorting scheme has been well developed (Maroušek, et. al. 2020). For example, a case study in Malaysia indicated that incineration for energy may produce highest income (with a net profit of 563083.40USD/day) followed by anaerobic digestion, gasification, and land fill gas recovery systems (Tan et al, 2015). However, Tan et al (2015) also indicated anaerobic digestion may be a more suitable technology than incineration for organic waste with high moisture content. Yet, a recent cost-benefit analyses done in Uganda indicated that despite low the LHV (6.12MJ/kg) in 85% of waste because of the water content in the biomass, the incineration for energy is still recommended as energy from compost may take much more work to harness (Amulen et al 2022). An evaluation by Chinese scholars in 2016 arrived similar conclusion indicating for composting, a finer classification of MSW may be needed which render incineration a more manageable and cost-effective technology considering all the emission reduced, and land resources saved (Zhao, et al., 2016). Not only for the global south, but some developed European countries also seem to have selected incineration for energy as their primarily means for waste management (Wang et al, 2022). This is not only incentivized by the policy requirement to reduce the landfill rates but the consideration of supplying suitable types of energy for the local demand: the Northern part of the European continent, in comparison the warmer regions, may be benefited more from both heat and electricity generated from an incinerator, especially during the cold season. This may not always be the case other countries under different climates.

The understanding and knowledge about the HV of the waste is in the heart of cost-and-benefit evaluations in waste management (Magrinho and Semiao 2008; Chen and Chen 2013). However, local socio-economic contexts and climatic conditions can alter the perceived value of energy generated through specific methods. Consequently, the types of waste in addition to HV may influence the strategies municipalities countries take to pursue a circular economy (Velvizhi et al, 2020). The low HV values in MSW found in lower income districts or municipalities have been linked to inadequate waste sorting or recycling behaviours, and the types of waste generated (Ozcan et al, 2016; Mondal and Kitawaki 2023). At a country level, regional variations in waste generation are apparent: developed countries like the USA produce up to 25% plastics waste, contrasting with emerging economies like China at about 10%. Over 60% of the waste generated in China is considered food waste or biomass, while the USA produces about 15% under this category (statistics in the World Bank as of 2023, https://datacatalog.worldbank.org/search/dataset/0039597). These geographical waste variations suggest that developed regions generate a higher proportion of waste suitable for energy incineration such as plastics, while emerging economies or less developed areas may require further assessment for energy recovery potential and methods. However, it is the less developed areas that may have been constrained by financial capacity to develop a strategy for waste management optimizing energy recovery and recycling benefits. This situation creates a lock-in effect, where opportunities to benefit from pursuing a circular economy approach are missed while environmental consequences persist. This might have also reflected in the underutilized energy potential from the MSW showed in a back-of-envelope calculation (section 1). International collaboration in developing waste management strategies for developing countries may be one of the solutions in bring the countries out of lock-in situation starting to practice circular economy, while mitigating environmental and climate issues.

4.6. Future outlooks

Characterization of MSW is the basis for decision-making and planning of MSW management, but the comprehensive profiling covering both physical and chemical properties of MSW may be partly constrain by financial capacity; the part of the information essential for an on-going management process are prioritized for collection. On the other hand, MSW physicochemical properties may be interrelated (Vargas-Moreno et al., 2012), allowing some extrapolation. For example, higher moisture content and bulk density of MSW are likely to be resulted from the presence of a high proportion of food waste; in this case, the energy recovery from the waste may be more appropriately done by other methods than incineration due to the high N and H content contents in the waste (Yousuf and Rahman, 2007). The appropriateness of using specific types of MSW as fuels may be determined based on the established understanding of such correlations of physiochemical properties and selective elements using proximate analysis or ultimate (Shen et al., 2010; Nhuchhen, 2016). On the other hand, the dynamic geographical, socioeconomic, policy, and management factors contribute to the increasing complexity and diversity of MSW composition, challenging the reliability of models based on historical data and categorized physical compositions. To forecast the potential changes of the composition in the MSW mixture and its associated HV during the lifespan of an incinerator, future research emphasizing developing HV prediction models by incorporating environmental, socioeconomic, and governance related parameters can be a practical alternative for facilitating the design of facilities.

Sections 2 and 3 outlined the variables and modelling techniques utilized for predicting HV. The choice of modelling approach often depends on data availability, researchers' skill-set, and intended applications. MRA, built relying on established physical-chemical theories, remains a mature and dominant method. The emerging AI-based approaches, not always produce results consist with combustion theories, offer advantages in handling dynamic MSW compositions (combustible and non-combustible) and potential nonlinear HV relationships with the compositions, though they require refined performance evaluation criteria and dataset size thresholds to avoid overfitting. As for the challenges of interpreting AI-based model, Explainable AI (XAI) appears as a potential solution, already applied in combustion-related research (e.g. Pandey, et al., 2023). Future prospects may witness the development of XAI-based HV prediction models for MSW.

Further, cross-referencing the model results derived from different set of variables may be beneficial for waste management decision-making during different phases of the life cycle of an incinerator (Table 1). As described previously, incorporating non-physiochemical parameters (like socio-economic and environmental factors) has potential to help better forecast waste generation changes and HV variations under defined scenarios. As the non-physical chemical factors may influence the waste compositions in an indirect and non-linear manner, AI-based modelling techniques may find an excellent niche application. It is expected and recommended that more investigation and analyses to be conducted towards this direction to make the non-physiological parameters utilized in HV prediction regularly.

5. Conclusions

MSW management should be part of plan for a sustainable and resilient city aiming to maximize resource recovery for local interests. The consequences of local MSW management collectively impacts the environment and human health across the border, making MSW management a global issue. Following the recently promoted concept of circular economy, energy resources in MSW will likely be exploited more in the future not only to reduce the use of fossil fuels and environmental protection but also to establish a sustainable local economy. Determining the HVs of MSW is essential for the designing and operating thermal MSW treatment processes. Case-specific prediction models have been regularly established, implying the need for tailored waste management strategies. However, some general trend in the relationship between explanatory variables and HV can be identified.

Over the last 3 decades, the physiochemical characteristics of MSW have been extensively used as the explanatory variables in HV prediction models for MSW based on the combustion theories. In addition to serving as the explanatory variables in the HV prediction models, the characteristics of MSW obtained from these analyses are by themselves important to support decision-making and planning, operating and maintaining the MSW management systems. The models in the literature revealed that the carbon-related variables (carbon element in ultimate analysis, FC in the proximate analysis, the carbon rich composition in the physical composition methods) are the major contributors to the HV. Hence, carbon is still the major source of the energy in the waste-to-energy technologies. Moisture contents as well as hydrate chemicals negatively impact the energy harvesting during incineration, making water in MSW is the major factor to manage and evaluate for incineration suitability. This review further identified socio-economic factors and environmental conditions emerging as meaningful explanatory variables for forecasting the influences of changing lifestyles and climates on MSW compositions and thus their HV within the lifespan of thermal treatment facilities.

Cumulative studies indicate nonlinear relationships among variables and HV. This, together with the increasing complexity of MSW compositions, makes AI-based approaches attractive in building better-fit HV prediction models. While AI models show promise, challenges like programming skills, data volume requirements, and interpretability hinder their widespread application. Until breakthroughs are made to overcome the current limitations, comparing results from MRA and AI approaches on the same dataset could enhance understanding and identify suitable models for case-specific waste management decisions and EfW technology applications.

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Appendix S1. Status of MSW incineration with/without energy recovery around the world.

Table S1. Status of MSW incineration with/without energy recovery around the world.

Country (year)	Number of plants		Total capacity (t/y)		Data source
	disposal	energy recovery	disposal	energy recovery	
Australia (2020)	17*		3909500*		[1]
Austria (2020)	1	60	100000	5122795	[2]
Belgium (2020)	48	247	1037947	8534038	[2]
Bulgaria (2020)	5	239	28470	1683059	[2]
China (2020)	95	536	34621345	228014405	[2]
Croatia (2020)	0	36	0	714311	[2]
Cyprus (2020)	0	1	0	131818	[2]
Czechia (2020)	21	59	115100	2902716	[2]
Denmark (2020)	2	27	186000	4367708	[2]
Estonia (2020)	2	53	50	592200	[2]
Finland (2020)	7	56	97603	A/N	[2]
France (2020)	29	90	2698000	12848730	[2]
Germany (2020)	50	837	4221772	68792929	[2]
Greece (2020)	151	32	26022	298902	[2]
Hungary (2020)	11	281	120847	2864632	[2]
Ireland (2020)	3	7	10850	1177875	[2]
Italy (2020)	90	349	10012483	12072597	[2]
Japan (2019)	687	380	177000		[3]
Latvia (2020)	2	1	A/N	150000	[2]
Lithuania (2020)	1	28	8000	427550	[2]
Luxembourg (2020)	0	6	0	1000000	[2]
Malta (2020)	1	0	7392	0	[2]
Netherlands (2020)	7	26	814750	10183026	[2]
Norway (2020)	3	19	32600	1737560	[2]
Poland (2020)	102	229	2319609	86914499	[2]
Romania (2020)	20	244	253183	7136591	[2]
Slovakia (2020)	3	17	78500	1071331	[2]
Slovenia (2020)	3	8	56580	326199	[2]
South Korea (2018)	262*		685098303*		[4]
Spain (2020)	61	103	239023	7710097	[2]
Sweden (2020)	30	115	244069	9750000	[2]
Thailand (2012）	3*		149650*		[5]
Turkey (2020)	7	40	757002	2520199	[2]
United Kingdom (2020)	91	40	12265362	11436948	[2]
United States (2018)	75*		94243*		[6]

* incineration for disposal or energy recovery is not indicated.

Supplementary Material

Appendix S2. Methodological framework.

Selection criteria of studies

The identification and selection of the studies were based on the keyword search of 'heating value', 'calorific value', or 'energy content' plus 'municipal solid waste' or 'waste' on web sources such as *China National Knowledge*, *Google Scholar, Web of Science* and *SCOPUS*, and also from the reference of the published studies of modeling heating value of MSW. The study focused on modelling heating value of MSW excluding studies on biomass, industrial waste, and single categories of waste (e.g., paper and plastics waste). In total, 49 studies modelling the heating value of MSW were used for the comparative analysis.

Review scheme

Numerous elements were reviewed for each of the identified studies: (1) LHV or HHV to be estimated, (2) basis of measurement, (3) unit to report the heating value, (4) variables used for model building, (5) data size used for model building and testing, (6) indicators to evaluation the performance of models, (7) the performance of the models, (8) model building techniques, and (9) study areas.

Supplementary Material

Appendix S3. Models for predicting HV of MSW.

Table S2. Summary of HV predictive models for MSW based on ultimate analysis.

Researcher	Model	Unit	Data size	Data source	City/country	Performance	Publication year	References
Wilson	$HV = 140.96\, C_{org} - 602.14\left(H - \frac{O}{8}\right) - 39.82S - 63.82\, C_{inorg} - 89.29 \times \frac{H - \frac{O}{8}}{2} - 31.37O -$	Btu/lb	22*	Experiment (SW)	U.S.	Min. residual: -398, max. residual:119	1972	[7]
Liu et al.	$LHV = 19.96C + 44.30O - 671.82S - 19.92Wa + 1558.80$	kcal/kg	40	Experiment	Kaohsiung, Taiwan, China	R^2: 0.926,	1996	[8]
Cooper et al.	$LHV_{dna} = 17050C + 32030\left(H - \frac{O}{8} - \frac{Cl}{35.5}\right) + 4591S - 791$	Btu/lb	40	Literature	-	R^2: 0.948	1999	[9]
Cooper et al.	$LHV_{dna} = 3918 + 12650C + 24340H - 9725O - 3240S - 5471Cl$	Btu/lb	40	Literature	-	R^2: 0.953	1999	[9]
Meraz et al.	$HHV = (1 - \frac{Wa}{100})(-0.3708C - 1.1124H + 0.1391O - 0.3178N - 0.1391S)$	MJ/kg	101*	Literature	-	MADR:1.0673	2003	[10]
Kathiravale et al.	$HHV_d = 416.638C - 570.017H + 259.031O + 598.955N - 5829.078$	kJ/kg	30	Experiment	Kuala Lumpur, Malaysia	R^2: 0.625, MPE: -0.59, stdev. PE: 9.5, Max. PE: 14.97, Min. PE: -22.65		[11]
Akkaya and Demir	$HHV = (1 - \frac{Wa}{100})(0.327C + 1.241H - 0.089O - 0.26N + 0.074S$	MJ/kg	100	Literature	-	R^2: 0.9826, AAE: 0.728%, SSE: 160.1, SEE:1.298	2009	[12]
Shi et al.	$HHV_d = -1.46 + 0.361C + 1.05H - 0.160N + 1.24S - 0.0658O$	MJ/kg	161	Literature + Experiment	Alberta, Canada	R^2: 0.938, R^2_{adj}: 0.936	2016	[13]
Shi et al.	$HHV_d = 0.349C + 1.01H - 0.174N + 0.886S - 0.0812O$	MJ/kg	161	Literature + Experiment	Alberta, Canada	R^2: 0.937, R^2_{adj}: 0.935,	2016	[13]
Shi et al.	$HHV_d = 0.353C + 1.01H - 0.130N - 0.0818O$	MJ/kg	161	Literature + Experiment	Alberta, Canada	R^2: 0.937, R^2_{adj}: 0.937,	2016	[13]
Shi et al.	$HHV_d = 0.35C + 1.01H - 0.826O$	MJ/kg	193	Literature + Experimen	Alberta, Canada	Training: R^2: 0.936, R^2_{adj}: 0.935, Validation: AAE: 6.73%, ABE: -1.78%	2016	[13]

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Eboh et al.	$HHV_d = 0.364C + 0.863H - 0.075O + 0.028N - 1.633S + 0.062Cl$	MJ/kg	86	Literature	-	R^2:0.95, AAE: 5.738%, ABE: 0.032%	2016	[14]
Han et al.	$HHV = 36C + 120H - 16O$	MJ/kg	14*	Literature	-	R^2:0.93, AAE: 6.47%, ABE: -6.21%	2017	[15]
Khuriati et al.	$HHV = 114.63C + 310.55H - 2762.68$	kcal/kg	29	Experiment	Semarang, Indonesia	R^2:0.98 , R^2_{adj}: 0.98 , MAPE：0.85%，RMSE：65	2017	[16]
Khuriati et al.	$HHV = 143.33C - 1737.55$	kcal/kg	29	Experiment	Semarang, Indonesia	R^2: 0.94 , R^2_{adj}: 0.94 , MAPE：1.35%，RMSE：99	2017	[16]
Ibikunle et al.	$HHV = 1.3849 + 85.0807C - 28.9675H - 666.125N + 11.6296S - 97.68O$	MJ/kg	62	Experiment	Ilorin, Nigeria	R^2: 0.837249, R^2_{adj}: 0.674498	2018	[17]
Boumanchar et al.	$HHV = 0.484C - 4.1307$	MJ/kg	187	Literature	-	Training: CC: 0.8852, RMSE：4.797; Validation: CC: 0.9426, RMSE：4.3251	2018	[18]
Boumanchar et al.	$HHV = 3.1451H - 0.8268$	MJ/kg	187	Literature	-	Training: CC: 0.8349, RMSE：5.676; Validation: CC: 0.7707, RMSE：7.4827	2018	[18]
Boumanchar et al.	$HHV = 0.3805C + 0.77H - 4.0219$	MJ/kg	187	Literature	-	Training: CC: 0.8897, RMSE：4.7084; Validation: CC: 0.9459, RMSE：4.3559	2018	[18]
Boumanchar et al.	$HHV = 2.775 + H + 0.004027C + 0.004027C^2 + \frac{0.05706}{H - 12.97} + \frac{0.02323}{H - 6.661} + \frac{0.009398}{H - 5.961} + \frac{1}{H^3}$	MJ/kg	187	Literature		Training: CC: 0.9375, RMSE：3.6391; Validation: CC: 0.9698, RMSE：2.8649	2018	[18]
Ibikunle et al.	$HHV = -7.9080 + 0.4699C + 0.9671H + 3.8402N - 0.5763N^2 - 12.924S + 6.8369S^2 - 0.$	MJ/kg	30	Experiment	Ilorin, Nigeria	R^2: 0.9768, R^2_{adj}: 0.9710, MSE : 1.9564, AIC: 133.2755, SBIC: 145.9437	2020	[19]
Amen et al.	$HHV = 4.392 + 2.514 \times 10^5 C^4 - 3.281 \times 10^{-30} C^{22}$	MJ/kg	36	Experiment	Lahore, Pakistan	R^2: 0.824	2021	[20]
Amen et al.	$HHV = 14.69 + 2.155C + 10.48HN + 0.03574M^2 - 0.8567M - 41.27N - 0.2534HM - 1.7$	MJ/kg	36	Experiment	Lahore, Pakistan	R^2: 0.668	2021	[20]
Amen et al.	$HHV = 11.8HS + 0.2367NO + 12.91N^2 - 0.3428 - 0.2871NM - 0.7196SM - 66.04NS$	MJ/kg	36	Experiment	Lahore, Pakistan	R^2: 0.644	2021	[20]
Amen et al.	$HHV = 5.734 + 41.96S + 0.9586CN + 0.4347ON^2 - 22.42N - 52.33NS - 0.01236CNM$	MJ/kg	36	Experiment	Lahore, Pakistan	R^2: 0.919	2021	[20]
Mateus et al.	$HHV_d = 0.486023C - 0.678825H - 0.62284O - 4.919720$	MJ/kg	443	Experiment	Portugal	R^2: 0.996, AAE: 1.57%, ABE: 0.02%, MAE: 0.42	2021	[21]
Mateus et al.	$HHV_d = 0.517692C + 0.720141H - 8.217007$	MJ/kg	443	Experiment	Portugal	R^2: 0.665, AAE: 1.91%, ABE: -0.19%, MAE: 0.48	2021	[21]

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Mateus et al.	$HHV_d = 0.254811C + 1.64176H$	MJ/kg	443	Experiment	Portugal	R^2: 0.992, AAE: 3.47, ABE: 1.02%, MAE: 0.91	2021	[21]
Mateus et al.	$HHV_d = 0.008854M + 0.492754C + 0.614578H - 0.057788O - 5.047684$	MJ/kg	443	Experiment	Portugal	R^2: 0.996, AAE: 1.55%, ABE: 0.02%. MAE: 0.41	2021	[21]
Mateus et al.	$LHV_d = 0.008859M + 0.492715C + 0.408739H - 0.057778O - 5.047003$	MJ/kg	443	Experiment	Portugal	R^2: 0.991, AAE: 1.65%, ABE: 0.03%. MAE: 0.41	2021	[21]
Mateus et al.	$LHV_d = 0.254799C + 1.435834H$	MJ/kg	443	Experiment	Portugal	R^2: 0.970, AAE: 3.69%, ABE: 1.10%. MAE: 0.91	2021	[21]
Mateus et al.	$LHV_d = 0.517644C + 0.514339H - 8.215895$	MJ/kg	443	Experiment	Portugal	R^2: 0.989, AAE: 1.81%, ABE: 0.03%. MAE: 0.41	2021	[21]
Mateus et al.	$LHV_d = 0.48598C + 0.473028H - 0.060077O - 4.918957$	MJ/kg	443	Experiment	Portugal	R^2: 0.990, AAE: 1.67%, ABE: 0.03%. MAE: 0.41	2021	[21]
Dashti et al.	$HHV = 0.0000426C^{2.9268} + 1.0827H^{1.0014} + 0.1941\,O - 4.9867\frac{O}{(C+H)^{0.7634}} + 11.0932$	MJ/kg	252	Literature	-	R^2: 0.972, MSE:1.9994, STD: 8.33, AARD: 5.13%	2021	[22]
Dashti et al.	$HHV = 1.65H + 0.3398N + 0.007172e^{s^2} + 0.003586(C - H - S)^2 - 0.003586CH - 0.0035$	MJ/kg	252	Literature	-	R^2: 0.9758, MSE:1.7379, STD: 8.24, AARD: 4.84%	2021	[22]
Siddiqui et al.	$HHV_w = 2090 - 100.31C - 61.16H + 1948.87N - 335.69S + 10.84A + 113.30\frac{C}{N}$	kJ/kg	48	Experiment	Delhi, India	RSS: 4131825.50, TSS: 5002382.61	2021	[23]
Siddiqui et al.	$LHV_w = 1382 - 53.32C + 61.89H + 1229.83N - 329.46S + 10.25A + 53.99\frac{C}{N}$	kJ/kg	48	Experiment	Delhi, India	RSS: 3810158.70, TSS: 4215731.75	2021	[23]
Siddiqui et al.	$HHV_w = 2496.43(C)^{-0.09406}H^{-0.14181}O^{-0.0985}N^{-0.09191}S^{-0.02833}A^{-0.0129}$	kJ/kg	48	Experiment	Delhi, India	AARE:6.5%	2021	[23]
Siddiqui et al.	$LHV_w = 78423.08(C)^{-0.50521}H^{-0.052302}O^{-0.62167}N^{-0.075378}S^{-0.06279}A^{-0.2735}$	kJ/kg	48	Experiment	Delhi, India	AARE:7.72%	2021	[23]
Kumar and Samadder	$LHV_w = 99.88 + 50.45C + 165.70H - 106.45N + 8.83O + 58.85S$	kcal/kg	28	Experiment	Dhanbad city, Jharkhand, India.	R^2: 0.834, MAPE: 2.807%, RMSE: 107.294	2023	[24]
Kumar and Samadder	$LHV_w = -1115.83 + 63.15C + 32.42H - 68.44N + 25.02O + 95.65S$	kcal/kg	28	Experiment	Dhanbad city, Jharkhand, India.	R^2: 0.884, MAPE: 2.6%, RMSE: 89.956	2023	[24]

Note: LHV = Lower heating value; LHV_d = Lower heating value at dry basis; dna = dry, no-ash basis; org = organic; inorg = inorganic; LHV_w = Lower heating value at wet basis; HHV = Higher heating value; HHV_d = Higher heating value at dry basis; HHV_{ad}= HHV on air-dried basis; C = Carbon, percentage by weight; H = Hydrogen, percentage by weight; O = Oxygen, percentage by weight; S = Sulfur, percentage by weight; Cl = Chlorine, percentage by weight; A = Ash content, percentage by weight; M = moisture content, percentage by weight at dry basis; R^2 = coefficient of determination; MADR = mean absolute deviation of residual; AAE: average absolute error; SSE: sum of square error; SEE = standard error of the estimate; R^2_{adj} = adjusted coefficient of determination; ABE: average bias error; MPE: mean percentage error; MAPE: mean

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absolute percentage error, RMSE: root mean square error; CC = correlation coefficient; MSE= mean square error; AIC: Akaike criterion; SBIC: Schwarz criterion; MAE: mean absolute error; AARD = average absolute relative deviation; STD = standard deviation; AARE = average absolute relative error; RSS = Residual sum of squares; TSS = Total sum of squares.

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Table S3. Summary of HV predictive models for MSW based on proximate analysis.

Researcher	Model	Unit	Data size	Data source	City/country	Performance	Publication year	References
Kathiravale et al.	$HHV_d = 356.248VM - 6998.497$	kJ/kg	30	Experiment	Kuala Lumpur, Malaysia	R^2: 0.682	2003	[11]
Kathiravale et al.	$HHV_d = 356.047VM - 118.035FC - 5600.613$	kJ/kg	30	Experiment	Kuala Lumpur, Malaysia	R^2: 0.691	2003	[11]
Ibikunle et al.	$HHV = 0.151721VM + 0.116768FC - 0.34728M - 7.19477$	MJ/kg	62	Experiment	Ilorin, Nigeria	R^2: 0.70493, R^2_{adj}: 0.52789	2018	[17]
Amen et al.	$HHV = 0.255085VM$	MJ/kg	36	Experiment	Lahore, Pakistan	R^2: 0.8184	2021	[20]
Amen et al.	$HHV = 0.744767 + 0.240652VM + \frac{5.214473}{VM^2}$	MJ/kg	36	Experiment	Lahore, Pakistan	R^2: 0.8184	2021	[20]
Amen et al.	$HHV = 0.184563VM + 3.570487$	MJ/kg	36	Experiment	Lahore, Pakistan	R^2: 0.8184	2021	[20]
Siddiqui et al.	$HHV_w = 3956 - 0.29M + 5.81FC - 11.05A$	kJ/kg	48	Experiment	Delhi, India	RSS: 4934875.09, TSS: 5002352.6	2021	[23]
Siddiqui et al.	$LHV_w = 3928 - 1.74M - 34.94FC - 19.01A$	kJ/kg	48	Experiment	Delhi, India	RSS: 3665011.67, TSS: 4215731.75	2021	[23]
Siddiqui et al.	$HHV_w = 12179.85(M)^{-0.27113}VM^{-0.24957}(FC)^{-0.15343}A^{-0.12424}$	kJ/kg	48	Experiment	Delhi, India	AARE:6.66%	2021	[23]
Siddiqui et al.	$lHV_w = 28127.79(M)^{-0.31913}VM^{-0.28581}(FC)^{-0.37883}A^{-0.18772}$	kJ/kg	48	Experiment	Delhi, India	AARE:7.18%	2021	[23]
Teshome et al.	$HHV_d = 212577VM + 147.076FC - 13795.987$	kcal/kg	13	Experiment	Yirgalem Town, Ethiopia	R^2: 0.78, MAPE: 1.93%	2023	[25]
Kumar and Samadder	$LHV_w = 588.44 + 42.74VM + 102.51FC - 6.50M$	kcal/kg	28	Experiment	Dhanbad city, Jharkhand, India.	R^2: 0.811, MAPE:3.2%, RMSE: 114.766	2023	[24]
Kumar and Samadder	$LHV_w = -2262.79 + 60.33VM + 155.22FC - 9.93M$	kcal/kg	28	Experiment	Dhanbad city, Jharkhand, India.	R^2: 0.839, MAPE: 2.723%, RMSE: 105.574	2023	[24]

Note: A = Ash content, percentage by weight; FC = Fixed carbon, percentage by weight; VM = Volatile combustible matter, percentage by weight; M = Moisture content, percentage by weight at dry basis; RSS = Residual sum of squares; TSS = Total sum of squares.

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Table S4. Summary of HV predictive models for MSW based on physical composition.

Researcher	Model	Unit	Data size	Data source	City/country	Performance	Publication year	References
Khan and Abu-Ghararah	$LHV = 23(Fo + 3.6Pa) + 160Pl$	Btu/lb	86	Literature	86 cities in 35 countries	R^2: 0.9711	1991	[26]
Liu et al.	$LHV_d = 88.2\,Pl + 40.5(Ga + Pa) - 6M$	kcal/kg	-	-	-		1996	[8]
Liu et al.	$LHV_d = 28.16\,Pl + 7.90Pa + 4.87Ga - 37.28M + 2229.91$	kcal/kg	34	Experiment	Kaohsiung, Taiwan, China	R^2: 0.967	1996	[8]
Liu et al.	$LHV_d = 30(Pl + Ru) + 15(Pa + Te + Wo) + 10Fo - 2.5M$	MJ/kg	40	Lab experiment	Shenzhen, China	Min. residual: -567, max. residual: 293; MAR: 387.4	1999	[27]
Liu et al.	$LHV_d = 28(Pl + Ru) + 12(Pa + Te + Wo + Fo) - 2.5M$	MJ/kg	40	Lab experiment	Shenzhen, China	Min. residual: -950, max. residual: 279; MAR: 404	1999	[27]
Liu et al.	$LHV_d = 16(Pl + Ru + Pa + Te + Wo + Fo) - 2.5M$	MJ/kg	40	Lab experiment	Shenzhen, China	Min. residual: -786, max. residual: 433; MAR: 397.4	1999	[27]
Abu-Qudais and Abu-Qdais	$LHV_w = 267.0({}^{Pl}/Pa) + 2285.7$	kcal/kg	15	Experiment (ASTM)(MSW)	Jordan	R^2: 0.940	2000	[28]
Tian et al.	$LHV_w = [458Pl + 141.1(Te + Fo + Pa + Yr) + 8.2A] \times \frac{100 - M}{100} - 25(M$	kJ/kg	N/A	Experiment	Beijing, China	PE: 0.03	2001	[29]
Dong and Jin	$LHV = 237.79Pl + 95.44Pa + 53.37Te + 18.77Wo + 4.33Fo + 1393.37$	kJ/kg	108	Experiment	Nanjing, China	-	2002	[30]
Kathiravale et al.	$LHV_W = 112.157Ga + 183.386Pa + 288.737Pl + 5064.701$	kJ/kg	30	Experiment (ASTM)(MSW)	Kuala Lumpur, Malaysia	R^2: 0.779; MPE: -0.49, stdev. PE: 8.88, Max. PE: 13.57, Min. PE: -16.46	2003	[11]
Kathiravale et al.	$LHV_W = 81.209Ga + 285.035Pl + 8724.209$	kJ/kg	30	Experiment	Kuala Lumpur, Malaysia	R^2: 0.645, MPE: -3.10, stdev. PE: 14.68, Max. PE: 18.27, Min. PE: -56.05	2003	[11]
Kathiravale et al.	$LHV_W = 112.815Ga + 184.366Pa + 298.343Pl - 1.920M + 5130.380$	kJ/kg	30	Experiment	Kuala Lumpur, Malaysia	R^2: 0.779	2003	[11]
Chang et al.	$LHV_d = (38.52Pa + 92.09Pl + 49.24Te + 38.34Wo + 37.55Fo + 64.07l$	kcal/kg	-	-	-	-	2007	[31]
Chang et al.	$LHV_d = (35.19Pa + 71.17Pl + 36.24Te + 48.06Wo + 42.21Fo + 44Mi)$	kcal/kg	180	Experiment	Taiwan, China	R: 0.9923, R^2: 0.9831, R^2_{adj} : 0.9827, MAPE: 5.56%, RPD: 5.6%	2007	[31]

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Chang et al.	$LHV_d = (39.04Pa + 101.47Pl + 38.47Fo)[(100 - M)/M) - 6M$	kcal/kg	180	Experiment	Taiwan, China	R: 0.9874, R²: 0.9753, R^2_{adj} : 0.9738, MAPE: 10.7%, RPD: 11.4%	2007	[31]
Lin et al.	$LHV_d = (47.3Pa + 58.6Pl + 38.6Te + 32.4Wo + 45.2Fo + 62.3Ru + 50$	kcal/kg	497	Experiment	Taiwan, China	R: 0.993, R²: 0.987, R^2_{adj} : 0.987, MAPE: 11.6%, ARPD: 10.4%	2013	[32]
Lin et al.	$LHV_w = 22.1Pa + 28.1Pl + 24.6Te + 12.7Wo + 6.0Fo + 57.4Ru + 17.2$	kcal/kg	497	Experiment	Taiwan, China	R: 0.976, R²: 0.954, R^2_{adj} : 0.953, MAPE: 17.7%, ARPD: 17.1%	2013	[32]
Lin et al.	$LHV_W = 219Pl + 109(Pa + Wo + Te)$	kJ/kg	113	Experiment + Literature	31 cities in China	Min. RE:-69.42%, max.RE: 67.79%, MAPE: 18.16%, SEE: 1111.44	2015	[33]
Khuriati et al.	$LHV = 2997 - 4.6\,Pa + 7Pl + 11Ru - 27Te + 20Wo - 28Yr - 26\,Fo -$	kcal/kg	24	Experiment	Semarang, Indonesia	R²: 0.491, R^2_{adj} : 0.22, RMSE:197	2015	[34]
Khuriati et al.	$LHV = 141 + 23\,Pa + 8Pl + 40Ru + 49Wo + 2.5\,Fo + 22Mi$	kcal/kg	24	Experiment	Semarang, Indonesia	R²: 0.491, R^2_{adj} : 0.31, RMSE:185	2015	[34]
Ozveren	$LHV_W = 20Fo + 83Pl + 187Pa + 105Wo + 170Te$	kJ/kg	89	Literature	-	R: 0.8205, MAPE:15%	2016	[35]
Nwankwo and Amah	$HHV = 17712.04Wo^{-0.0094}Fo^{-0.0063}Le^{0.041}Mi^{-0.019}Pa^{-0.044}Pl^{0.084}Te^{0.0}$	kJ/kg	10	Experiment	Port Harcourt	Min residual: -60.723, Max residual: 26.928, R²: 0.994	2016	[36]
Nwankwo and Amah	$HHV = 22402 - 25.677Fo + 122.132Le - 56.697Mi - 104.471Pa + 4$	kJ/kg	10	Experiment	Port Harcourt	Min residual: -23.351, Max residual: 25.684, R²: 0.999	2016	[36]
Oumarou et al.	$HHV_d = 1.0325 - 0.0011Wo + 0.2254Gr - 0.0046Pa - 0.0068L + 0.31$	MJ/kg	9	Experiment	Northern Nigeria	STD:5.29%	2016	[37]
Su et al.	$LHV = 2494.019 - 22.833M - 5.223Ga - 0.926Pa + 2.129Pl$	kcal/kg	48	Experiment	China	MAPE: 15.78%	2016	[38]
Drudi et al.	$LHV_W = (13.69Or + 20.94Sa + 37.99Pl + 10.48Pa + 19.27Te)(1 - M)$	MJ/kg	60	Experiment (MSW)	Santo Andre, Brazil	R: 0.9964 R²: 0.9928, R^2_{adj} : 0.9741, Error: 1.4715, STD: 1.77, MAPE: 6.48%	2017	[39]
Ibikunle et al.	$HHV = 0.171002 + 0.010962Ga + 0.008254Ce + 0.010242Po$	MJ/kg	62	Experiment	Ilorin, Nigeria	R²: 0.976923, R^2_{adj}: 0.959616	2018	[17]
Drudi et al.	$LHV_w = (16.55Or + 20.42Sa + 36.17Pl + 9.06Pa + 22.81Te)(1 - M) -$	MJ/kg	36	Experiment (ASTM)(MSW)	Santo Andre, Brazil	R²: 0.9963, R^2_{adj}: 0.9635, MAPE: 5.09%, ABE: 0.56%, MSE: 1.10, AMD: 0.84	2019	[40]
Drudi et al.	$LHV_w = (15.42Or + 19.14Sa + 32.68Pl + 8.33Pa + 21.51Te)(1 - M) -$	MJ/kg	36	Experiment	Santo Andre, Brazil	R²: 0.9958, R^2_{adj}: 0.9630, MAPE: 5.52%, ABE: 0.54%, MSE: 1.07, AMD: 0.84	2019	[40]
Li	$LHV_w = 5529.832 - 59.618Fo + 87.144Mi + 78.874Pl - 118.693M +$	kJ/kg	108	Experiment	Beijing, China	R: 0.986 R²: 0.972, R^2_{adj} : 0.971, SEE: 220.18696	2019	[41]

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Lv	$LHV_w = \frac{100 - M}{100}(145.6Fo + 160.8Pa + 269.9Pl + 195.5Te) - 10.3M -$	kJ/kg	100	Experiment	Guangzhou, China	Relative error < 10%	2020	[42]
Wang et al.	$LHV = -68.06Fo + 91.77Pa + 52.65Pl + 30.73Te + 34.91Wo + 7342.7$	kJ/kg	151	Literature	44 cities in 11 countries	R: 0.73, MAPE: 22.18, SEE:1414.69, Min. residual: -3003.60, max. residual: 3117.46, std. residual: 759.64	2021	[43]
Wang et al.	$LHV = -74.42Fo + 83.20Pa + 67.90Pl + 7669.08$	kJ/kg	151	Literature	44 cities in 11 countries	R: 0.73, MAPE: 21.94, SEE: 1410.36, Min. residual: -3401.10, max. residual: 3352.51, std. residual: 803.07	2021	[43]
Janna et al.	$HHV_d = 163.935Fo + 364.546Pl + 180.523Pa + 195.735Wo + 214.18$	kJ/kg	60	Literature + Assumptions	-	R^2: 1	2021	[44]
Janna et al.	$HHV_d = 164.841Fo + 365.184Pl + 181.155Pa + 196.394Wo + 214.83$	kJ/kg	60	Literature + Assumptions	-	R^2: 1	2021	[44]
Janna et al.	$HHV_w = 329.88Pl + 152.689Pa + 154.004Wo + 167.338Te + 3674.33$	kJ/kg	60	Literature + Assumptions	-	R^2: 0.99	2021	[44]
Janna et al.	$HHV_w = 247.892Pl + 70.306Pa + 71.092Wo + 84.433Te - 101.071M$	kJ/kg	60	Literature + Assumptions	-	R^2: 0.99	2021	[44]
Siddiqui et al.	$HHV_w = 4934 + 0.18Bd - 15.78Fo - 61.63Gd - 5.95Pa - 19.26Wo +$	kJ/kg	-	Literature	India	A/N	2021	[23]
Siddiqui et al.	$LHV_w = 4061 + 0.43Bd - 21.44Fo - 29.67Gd + 1.68Pa + 2.14Wo + 1$	kJ/kg	-	Literature	India	A/N	2021	[23]
Kumar and Samadder	$LHV_w = 1225.85 + 18.79Fo + 19.88Yr + 52.02Pl + 7.07Pa + 41.96(Te$	kcal/kg	28	Experiment	Dhanbad city, Jharkhand, India.	R^2: 0.906, MAPE:2.278%, RMSE: 80.662	2023	[24]
Kumar and Samadder	$LHV_w = 838.09 + 21.50Fo + 26.76Yr + 58.53Pl + 11.46Pa + 37.05(Te$	kcal/kg	28	Experiment	Dhanbad city, Jharkhand, India.	R^2: 0.912, MAPE: 2.237%, RMSE: 78.436	2023	[24]
Mondal and Kitawaki	$LHV_w = 7.721 + 0.034Fo + 0.074Pa + 0.071Wo + 0.077Te + 0.104Ru$	MJ/kg	90	Experiment	Dhaka, Bangladesh	R^2: 0.9987, R^2_{adj}: 0.9986, MAPE: 0.959%, SEE: 0.065	2023	[45]
Mondal and Kitawaki	$LHV_w = 7.660 + 0.038Fo + 0.075(Pa + Wo + Te) + 0.112(Ru + Pl) -$	MJ/kg	90	Experiment	Dhaka, Bangladesh	R^2: 0.9986, R^2_{adj}: 0.9985, MAPE: 0.978% , SEE: 0.069	2023	[45]
Mondal and Kitawaki	$LHV_w = 7.695 + 0.034Fo + 0.074Pa + 0.071Wo + 0.077Te + 0.121(Ru$	MJ/kg	90	Experiment	Dhaka, Bangladesh	R^2: 0.9986, R^2_{adj}: 0.9986, MAPE: 1.024% , SEE: 0.9987	2023	[45]
Mondal and	$LHV_w = 8.220 + 0.032Fo + 0.070Pa + 0.068Wo + 0.073Te + 0.121Pl -$	MJ/kg	90	Experimen	Dhaka,	R^2: 0.9970, R^2_{adj}: 0.9968, MAPE:	2023	[45]

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Kitawaki	t	Bangladesh	1.370% , SEE: 0.100

Note: LHV = Lower heating value; LHV_d = Lower heating value at dry basis; LHV_w = Lower heating value at wet basis; HHV = Higher heating value; HHV_d = Higher heating value at dry basis; HHV_{ad}= HHV on air-dried basis; M = Mmoisture content, percentage by weight at dry basis; Pl = Plastics, percentage by weight; L = Leaves, percentage by weight; Le = Leather, percentage by weight; Pa = Paper and cardboard, percentage by weight; Wo = Wood, percentage by weight; Yr = yard waste, percentage by weight; Gr = Grass, percentage by weight; Ga = Garbage, percentage by weight; Gd = Garden waste, percentage by weight; Gl = Glass, percentage by weight; Fo = Food, percentage by weight; Te = Textile, percentage by weight; Me = Metal, percentage by weight; Mi = Miscellaneous components, percentage by weight; Ru = Rubber and leather, percentage by weight; Or = Organic waste, percentage by weight; Sa = Sanitary waste, percentage by weight; Ce = Cellulose, percentage by weight; Po = Polyethylene, percentage by weight; Ot = Other waste, percentage by weight; Br = Bricks, percentage by weight; Bd = Bulk density (kg m^{-3}) ; Nb = Non-biodegradable waste, percentage by weight. MAR = mean absolute residual; R= coefficient of correlation; RPD= relative percentage deviation; RE = relative error; ARPD = average relative percentage deviation; AMD = absolute mean deviation.

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Table S5. Summary of AI-based models for predicting the HV of MSW.

Researcher	Predictors (wt.%)	Response	Unit	Method	Data size	Data allocation [a]	Data source	City/Country	Performance	Publication year	References
Dong et al.	Plastic, paper, textile, grass, food	LHV	kJ/kg	FFNN	108	108:0:0	Experiment	Nanjing, China	only four groups' relative error of data are higher than 5%	2003	[46]
Shu et al.	C, H, N, O, S, Cl	LHV	kcal/kg	MLPNN	220	110:55:55	Experiment	Taiwan, China	All data: R^2: 0.93, MAE: 105.45, RMSE: 146.75, IA: 0.98; Training: R^2: 0.93, MAE: 104.3, RMSE: 143.9, IA: 0.98; Validation: R^2: 0.93, MAE: 128.6, RMSE: 170.5, IA: 0.98; Testing: R^2: 0.93, MAE: 106.7, RMSE: 148.7, IA: 0.98;	2006	[47]
Shu et al.	moisture, plastics, paper, food waste, miscellaneous organics, textile, leather & rubber; other combustible composition, noncombustible composition	LHV	kcal/kg	MLPNN	220	110:55:55	Experiment	Taiwan, China	All data: R^2: 0.87, MAE: 156.38, RMSE:203.75 , IA: 0.97; Training: R^2: 0.88, MAE: 143.4, RMSE: 191.2, IA: 0.97; Validation: R^2: 0.87, MAE: 173.3, RMSE: 222.5, IA: 0.97; Testing: R^2: 0.86, MAE: 165.5, RMSE: 208.4, IA: 0.96;	2006	[47]
Shu et al.	plastics, paper, food waste, miscellaneous organics, textile, leather, and rubber; other combustible composition, non-combustible composition; moisture content	LHV	kcal/kg	MLPNN	220	110:55:55	Experiment	Taiwan, China	All data: R^2: 0.84, MAE: 171.50, RMSE: 225.44, IA: 0.96; Training: R^2: 0.86, MAE: 155.9, RMSE: 204.8, IA: 0.96; Validation: R^2: 0.84, MAE: 192.5, RMSE: 248.2, IA: 0.95; Testing: R^2: 0.82, MAE: 181.7, RMSE: 240.4, IA: 0.95;	2006	[47]
Shu et al.	moisture, combustible matter (volatile matter and fixed carbon), and ash	LHV	kcal/kg	MLPNN	220	110:55:55	Experiment	Taiwan, China	All data: R^2: 0.83, MAE: 175.83, RMSE: 232.9, IA: 0.95; Training: R^2: 0.82, MAE: 172.5, RMSE: 227.9, IA: 0.95; Validation: R^2: 0.86, MAE: 169.7, RMSE: 229.6, IA: 0.96; Testing: R^2: 0.81, MAE: 188.6, RMSE: 245.6, IA: 0.95;	2006	[47]
Akkaya and Demir	C, H, O, N, S, ash and moisture content	HHV	MJ/kg	ANN	100	50:25:25	Literature	-	All data: R:0.99144, Training: R: 0.99779, validation: R: 0.9761, Test: R: 0.9923	2009	[12]
Zhang et al.	Plastic & rubber, paper, textile, wood, food waste, metal, glass, ash, moisture content	LHV	kJ/kg	BPNN	17	14:0:3	Literature	China	Testing: ARE: 8.03 – 11.03%	2010	[48]
Ogwueleka and Ogwueleka	Plastic, Paper, Textile, glass, food	LHV	kJ/kg	ANN	60	37:23:0	Experiment	Abuja, Nigeria	Training: R^2: 0.992, MAPE: 9.13%; Validation: R^2: 0.981, MAPE: 9.60%	2010	[49]
Khuriati et al.	Paper, plastic, rubber, textile, wood, yard waste, food & kitchen waste, miscellaneous combustible waste	LHV	kcal/kg	BPNN	24	24:0:0	Experiment	Semarang, Indonesia	R: 0.9763	2015	[34]

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Ozveren	Food, paper, plastic, textile, wood, moisture	LHV	kJ/kg	ANN	89	71:0:18	Literature	China	R: 0.9933, MAPE:8%	2016	[35]
Ding et al.	The wet weight of LDPE, HDPE, PP, PS, PET, PVC, PC & other plastics, paper, textile, rubber, wood and leather, moisture content, the content of hydrogen at dry basis	LHV	kJ/kg	BPNN	78	71:7:0	Experiment	Chengdu, China	Training: CC: 0.9693, MAE:596.3202, RMSE:733.6562, ARE: 27.0542%, RARE: 24.7623%; Validation: ARE: 6.28%.	2016	[50]
Ding et al.	The wet weight of LDPE, HDPE, PP, PS, PET, PVC, PC & other plastics, paper, textile, rubber, wood and leather, moisture content, the content of hydrogen at dry basis	LHV	kJ/kg	RBFNN	78	71:7:0	Experiment	Chengdu, China	Training: CC: 0.9790, MAE:468.7852, RMSE:603.7651, ARE: 21.2681%, RARE: 20.3782%; Validation: ARE: 2.79%.	2016	[50]
Ding et al.	The wet weight of LDPE, HDPE, PP, PS, PET, PVC, PC & other plastics, paper, textile, rubber, wood and leather, moisture content, the content of hydrogen at dry basis	LHV	kJ/kg	ANFIS	78	71:7:0	Experiment	Chengdu, China	Training: MSE:49.3478, RMSE:7.0248; Validation: ARE: 2.79%.	2016	[50]
Gong et al.	C, H, O, N, S, ash and moisture content	HHV	MJ/kg	RBFNN	100	75:0:25	Literature	-	Training: R^2: 0.99756, MSE: 0.227391, AARD: 5.477973%; Testing: R^2: 0.996938, MSE: 0.248202, AARD: 5.171256%; All: R^2: 0.997483, MSE: 0.232594, AARD: 5.401294%;	2017r	[51]
Drudi et al.	Organic matter, plastics, paper, sanitary and textiles	HHV	MJ/kg	MLPNN	36	26:10:0	Experiment	Santo André, Brazil	Average deviation: 2.349, MAPE: 12.9%, MSE: 6.511	2017	[52]
Drudi et al.	Organic matter, plastics, paper, sanitary, textiles	HHV	MJ/kg	ELM	36	26:10:0	Experiment	Santo André, Brazil	Average deviation: 0.862, MAPE: 4.84%, MSE: 0.965	2017	[52]
Singh et al.	C, H, O, N, S, P, K, ash	HV	Kcal/gm	ANN	39	27:6:6	Experiment	Ghaziabad City, India	All data: R: 0.9088; Training: R:0.9907, MSE: 0.0037; Validation: R: 0.9226; Testing: R: 0.8632	2018	[53]
Baghban and Ebadi	C, H, O, N, S, ash, moisture content	HHV	MJ/kg	GA-ANFIS	100	75:0:25	Literature	-	Training: R^2: 0.9948; Testing: R^2: 0.9983	2019	[54]
Olatunji et al.	C, H, O, N, S, ash, moisture content	HHV	MJ/kg	LM-MLPNN	123	86:12:25	Literature	-	MAD:2.409, RMSE:3.587, MAPE: 21.68%, CC:0.97	2019	[55]
Olatunji et al.	C, H, O, N, S, ash and moisture content	HHV	MJ/kg	RP-MLPNN	123	86:12:25	Literature	-	MAD:0.328, RMSE:3.095, MAPE: 22.483%, CC:0.986	2019	[55]
Adeleke, et al.	Organics, paper, plastic, textile, glass, metal	LHV	MJ/kg	ANN	66	46:0:20	Experiment	Johannesburg, South Africa	Training: RMSE: 0.0279, MAD: 0.0178, MAPE: 0.886, R: 0.9999; Testing: RMSE: 0.5168, MAD: 0.3051, MAPE: 12.7157, R: 0.9660	2020	[56]
Adeleke, et	Organics, paper, plastic,	LHV	MJ/kg	ANFIS-	66	46:0:20	Experiment	Johannesburg, South	Training: RMSE: 4.16×10^{-7}, MAD: 1.88×10^{-7}, MAPE: 5.03×10^{-6}, R: 1.000; Testing: RMSE:	2020	[56]

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al.	textile, glass, metal			SC				Africa	0.2916, MAD: 0.2286, MAPE: 8.4736, R: 0.9731		
Adeleke, et al.	Organics, paper, plastic, textile, glass, metal	LHV	MJ/kg	ANFIS-GP	66	46:0:20	Experiment	Johannesburg, South Africa	Training: RMSE: 8.61×10^{-8}, MAD: 0.64 ×10^{-8}, MAPE: 1.77 ×10^{-6}, R: 1.000; Testing: RMSE: 0.1944, MAD: 0.1389, MAPE: 4.2982, R: 0.9874	2020	[56]
Adeleke, et al.	Organics, paper, plastic, textile, glass, metal	LHV	MJ/kg	ANFIS-FCM	66	46:0:20	Experiment	Johannesburg, South Africa	Training: RMSE: 1.56×10^{-7}, MAD: 1.08 ×10^{-7}, MAPE: 2.9 ×10^{-6}, R: 1.000; Testing: RMSE: 0.1944, MAD: 0.1389, MAPE: 4.2982, R: 0.9874	2020	[56]
Wang et al.	Food, paper, plastic, textile, wood	LHV	kJ/kg	ANN	151	100:51:0	Literature	44 cities in 11 countries	MAPE: 18.38%, SEE: 1296.94, Min. residual: -2183.37, max. residual: 4261.35, std. residual: 1246.94	2021	[56]
Wang et al.	Food, paper, plastic	LHV	kJ/kg	ANN	151	100:51:0	Literature	44 cities in 11 countries	MAPE: 15.92%, SEE: 1357.92, Min. residual: -2960.11, max. residual: 4171.90, std. residual: 1301.92	2021	[43]
Dashti et al.	C, H, O, N, S	HHV	MJ/kg	PSO-ANFIS	252	176:0:76	Literature	-	All data: R^2: 0.9853, MSE:1.0514, STD: 8.34, AARD: 3.24%; Training: R^2: 0.9646, MSE:3.2003, STD: 9.03, AARD: 6.48%; Test: R^2: 0.9922, MSE:0.5195, STD: 8.15, AARD: 2.43%	2021	[22]
Dashti et al.	C, H, O, N, S	HHV	MJ/kg	GA-RBF	252	176:0:76	Literature	-	All data: R^2: 0.9528, MSE:3.7507, STD: 8.83, AARD: 4.25%; Training: R^2: 0.8886, MSE:15.7302, STD: 11.15, AARD: 7.69%; Test: R^2: 0.9883, MSE: 0.7855, STD: 8.13, AARD: 3.40%	2021	[22]
Dashti et al.	C, H, O, N, S	HHV	MJ/kg	CMIS	252	176:0:76	Literature	-	All data: R^2: 0.9814, MSE:1.3283, STD: 8.38, AARD: 4.07%; Training: R^2: 0.9854, MSE:1.3881, STD: 9.07, AARD: 4.31%; Test: R^2: 0.9805, MSE:1.3135, STD: 8.19, AARD: 4.01%	2021	[22]
Birgen et al.	Temperature, precipitation, wind strength, day of the week, week of the year	LHV	MJ/kg	GPR ML	1024	730:294:0	Observations and calculations	Kristiansand, Norway	Training: MAE: 0.469; Validation: MAE: 0.688, MAPE: 6.05%.	2021	[57]
Baghban and Shamshirband	C, H, O, N, S, ash, moisture content	HHV	MJ/kg	MLPNN	100	75:0:25	Literature	-	Training: MSE: 0.48228, AARD: 0.360286%, R^2: 0.997483; Testing: MSE: 0.2326, R^2:0.997	2022	[58]
Baghban and Shamshirband	C, H, O, N, S, ash, moisture content	HHV	MJ/kg	LSSVM	100	75:0:25	Literature	-	Training: MSE: 0.01362, AARD: 0.012572%, R^2: 0.999998; Testing: MSE: 0.0002, R^2:1.000	2022	[58]

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Dong et al.	C, N	HHV	kcal/kg	OGM	15	10:5:0	Experiment	Shannxi, China	Training: MAPE: 11.12%; Validation: MAPE: 25.16%	2022	[59]
Dong et al.	C, N, Cl	HHV	kcal/kg	OGM	15	10:5:0	Experiment	Shannxi, China	Training: MAPE: 9.27%; Validation: MAPE: 15.98%	2022	[59]
Dong et al.	C, N, Cl, H	HHV	kcal/kg	OGM	15	10:5:0	Experiment	Shannxi, China	Training: MAPE: 7.72%; Validation: MAPE: 14.64 %	2022	[59]
Dong et al.	C, N, Cl, H, O	HHV	kcal/kg	OGM	15	10:5:0	Experiment	Shannxi, China	Training: MAPE: 4.90%; Validation: MAPE: 38.33%	2022	[59]
Dong et al.	A, FC, VM	HHV	kcal/kg	OGM	15	10:5:0	Experiment	Shannxi, China	Training: MAPE: 5.42%; Validation: MAPE: 2.89%	2022	[59]
Dong et al.	A, FC, VM, moisture content	HHV	kcal/kg	OGM	15	10:5:0	Experiment	Shannxi, China	Training: MAPE: 5.41%; Validation: MAPE: 3.06%	2022	[59]
Taki and Rohani	C, H, O, N, S, ash, moisture content	HHV	MJ/kg	RBFNN	100	-	Literature	-	Training: RMSE： 0.02, MAPE: 0.23%, R^2: 0.99; Test: RMSE： 0.03, MAPE: 0.32%, R^2: 0.99; Total: RMSE： 0.03, MAPE: 0.25%, R^2: 0.99	2022	[60]
Taki and Rohani	C, H, O, N, S, ash, moisture content	HHV	MJ/kg	MLPNN	100	-	Literature	-	Training: RMSE： 0.71, MAPE: 4.79%, R^2: 0.99; Test: RMSE： 1.93, MAPE: 17.33%, R^2: 0.96; Total: RMSE： 1.07, MAPE: 7.30%, R^2: 0.99	2022	[60]
Taki and Rohani	C, H, O, N, S, ash, moisture content	HHV	MJ/kg	SVM	100	-	Literature	-	Training: RMSE： 0.67, MAPE:11.75%, R^2: 0.99; Test: RMSE： 1.13, MAPE: 11.88%, R^2: 0.99; Total: RMSE ： 0.78, MAPE: 11.77%, R^2: 0.99	2022	[60]
Taki and Rohani	C, H, O, N, S, ash, moisture content	HHV	MJ/kg	ANFIS	100	-	Literature	-	Training: RMSE： 1.79, MAPE: 23.1%, R^2: 0.97; Test: RMSE： 1.36, MAPE: 26.41%, R^2: 0.98; Total: RMSE ： 1.71, MAPE:23.76%, R^2: 0.97	2022	[60]
Taki and Rohani	C, H, O, N, S, ash	HHV	MJ/kg	RBFNN	100	-	Literature	-	Training: RMSE： 0.35, MAPE: 2.13%, R^2: 0.99; Test: RMSE： 0.41, MAPE: 2.33%, R^2: 0.99; Total: RMSE： 0.36, MAPE: 2.32%, R^2: 0.99	2022	[60]
Taki and Rohani	H, O, N, S, ash, moisture content	HHV	MJ/kg	RBFNN	100	-	Literature	-	Training: RMSE： 0.25, MAPE: 2.42%, R^2: 0.99; Test: RMSE： 0.21, MAPE: 2.98%, R^2: 0.99; Total: RMSE： 0.25, MAPE: 2.53%, R^2: 0.99	2022	[60]
Taki and Rohani	C, O, N, S, ash, moisture content	HHV	MJ/kg	RBFNN	100	-	Literature	-	Training: RMSE： 0.11, MAPE: 1.31%, R^2: 0.99; Test: RMSE： 0.14, MAPE: 1.55%, R^2: 0.99; Total: RMSE： 0.12, MAPE: 1.36%, R^2: 0.99	2022	[60]

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Taki and Rohani	C, H, N, S, ash, moisture content	HHV	MJ/kg	RBFNN	100	-	Literature	-	Training: RMSE： 0.07, MAPE: 1.08%, R^2: 0.99; Test: RMSE： 0.11, MAPE: 0.72%, R^2: 0.99; Total: RMSE： 0.08, MAPE: 1.01%, R^2: 0.99	2022	[60]
Taki and Rohani	C, H, O, S, ash, moisture content	HHV	MJ/kg	RBFNN	100	-	Literature	-	Training: RMSE： 0.09, MAPE: 0.95%, R^2: 0.99; Test: RMSE： 0.15, MAPE: 0.85%, R^2: 0.99; Total: RMSE： 0.18, MAPE: 0.67%, R^2: 0.99	2022	[60]
Taki and Rohani	C, H, O, N, ash, moisture content	HHV	MJ/kg	RBFNN	100	-	Literature	-	Training: RMSE： 0.23, MAPE: 2.89%, R^2: 0.99; Test: RMSE： 0.27, MAPE: 3.57%, R^2: 0.99; Total: RMSE： 0.23, MAPE: 3.02%, R^2: 0.99	2022	[60]
Taki and Rohani	C, H, O, N, S, moisture content	HHV	MJ/kg	RBFNN	100	-	Literature	-	Training: RMSE： 0.07, MAPE: 0.90%, R^2: 0.99; Test: RMSE： 0.13, MAPE: 0.65%, R^2: 0.99; Total: RMSE： 0.08, MAPE: 0.57%, R^2: 0.99	2022	[60]
Adeleke, et al.	Organics, paper, plastic, textile, glass, metal	LHV	MJ/kg	Standalone ANFIS	40	-	Experiment	Johannesburg, South Africa	R^2: 0.988, RMSE: 0.191, MAPE: 4.238%, MAD: 0.147	2022	[61]
Adeleke, et al.	Organics, paper, plastic, textile, glass, metal	LHV	MJ/kg	PSO-ANFIS	40	-	Experiment	Johannesburg, South Africa	R^2: 0.994, RMSE: 0.139, MAPE: 2.536%, MAD: 0.064	2022	[61]
Adeleke, et al.	Organics, paper, plastic, textile, glass, metal	LHV	MJ/kg	GA-ANFIS	40	-	Experiment	Johannesburg, South Africa	R^2: 0.975, RMSE: 0.178, MAPE: 3.346%, MAD: 0.085	2022	[61]
Du and Niu	Food, paper, plastics & rubber, textile, wood & bamboo, dirt, bricks, glass, metal, others, miscellaneous	LHV	kJ/kg	ANN	20	-	Experiment	Shanghai, China	MAPE:7.76%, RMSE:0.53	2022	[62]
Kumar and Samadder	Food, yard waste, plastics, paper &cardboard, textile & rubber, metal & glass, others	LHV	kcal/kg	ANN	28	-	Experiment	Dhanbad city, Jharkhand, India.	R^2:0.887, MAPE: 2.342%, RMSE: 88.156	2023	[24]
Kumar and Samadder	Food, yard waste, plastics, paper &cardboard, textile & rubber,	LHV	kcal/kg	ANN	28	-	Experiment	Dhanbad city, Jharkhand, India.	R^2: 0.914, MAPE: 2.442%, RMSE: 82.123	2023	[24]
Kumar and Samadder	FC, VM, moisture content	LHV	kcal/kg	ANN	28	-	Experiment	Dhanbad city, Jharkhand, India.	R^2: 0.813, MAPE: 3.356%, RMSE: 114.779	2023	[24]
Kumar and	FC, VM, moisture content	LHV	kcal/kg	ANN	28	-	Experiment	Dhanbad city,	R^2: 0.814, MAPE:3.286 %, RMSE: 113.833	2023	[24]

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Samadder								Jharkhand, India.			
Kumar and Samadder	C, H, O, N, S	LHV	kcal/kg	ANN	28	-	Experiment	Dhanbad city, Jharkhand, India.	R^2: 0.734, MAPE: 3.633%, RMSE: 135.99	2023	[24]
Kumar and Samadder	C, H, O, N, S	LHV	kcal/kg	ANN	28	-	Experiment	Dhanbad city, Jharkhand, India.	R^2: 0.912, MAPE: 2.11%, RMSE: 78.317	2023	[24]
Jose and Sasipraba	C, H, O, N, S, ash, moisture content	HHV	MJ/kg	GP	25	-	Experiment	Chennai, Tamil Nadu, India	RMSE: 2.87, CC: 0.972	2023	[63]
Jose and Sasipraba	C, H, O, N, S, ash, moisture content	HHV	MJ/kg	RP	25	-	Experiment	Chennai, Tamil Nadu, India	RMSE: 3.59, MAD: 2.41, MAPE: 21.68%, CC: 0.988	2023	[63]
Jose and Sasipraba	C, H, O, N, S, ash, moisture content	HHV	MJ/kg	LM	25	-	Experiment	Chennai, Tamil Nadu, India	RMSE: 3.10, MAD: 0.33, MAPE: 22.48%, CC: 0.988	2023	[63]
Jose and Sasipraba	C, H, O, N, S, ash, moisture content	HHV	MJ/kg	DSVM	25	-	Experiment	Chennai, Tamil Nadu, India	RMSE: 3.05, MAD: 0.3, MAPE: 34.56%, CC: 0.991	2023	[63]
Jose and Sasipraba	C, H, O, N, S, ash, moisture content	HHV	MJ/kg	ODL	25	-	Experiment	Chennai, Tamil Nadu, India	RMSE: 2.782, MAD: 0.294, MAPE: 37.41, CC: 0.995	2023	[63]
Tao et al.	Images of MSW samples	LHV	MJ/kg	ANN	120	90:0:30	Experiment	Northeast China	MAPE: 9.5%	2023	[64]

Note: [a] The data application expressed as: training data: validation data: testing data. FFNN = feed forward neural networks; MLPNN = multilayer perceptron neural networks; MAE = mean absolute error; IA = index of agreement; BPNN = back propagation neural networks; ARE = absolute relative error; RBFNN = radical basis function neural networks; ANFIS = adaptive neural fuzzy inference system; RARE = root absolute relative error; MAD = mean absolute deviation; ELM = extreme learning machine; LSSVM = least squares support vector machine; (D)SVM = (Deep) support vector machine; LM = Levenberg-Marquardt; RP = resilient backpropagation; GA = genetic algorithm; GP = grid partitioning; SC = subtractive clustering; FCM = Fuzzy c-means clustering; PSO = Particle swarm optimization; CMIS = committee machine intelligent system; GPR ML = gaussian processes regression machine learning; OGM = Optimized grey forecasting model; ODL = Optimal deep learning;

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Appendix S4. Equations converting HHV and LHV.

Relationships between HHV and LHV can be described based on Equation (1) recommended by IPCC [65].

$$\mathrm{LHV}\ (\mathrm{MJ}/kg) = \mathrm{HHV}\ (\mathrm{MJ}/kg) - 0.212H - 0.0245M - 0.008O \qquad (1)$$

Where HHV is the higher heating value measured under laboratory conditions, LHV is the lower heating value, H is the percentage of hydrogen, M is moisture content (%), and O is the percentage of oxygen.

In practice, sampling approach and waste categories vary among countries and local authorities, and thus the conversion methods need to be specifically adjusted. Researches following the standard sampling and test methods from ASTM (e.g. ASTM D5468-02) adopt Equation (2) [67]. Chinese researchers normally use the Equations (3 – 5) in the national standard methods CJ/T 313 – 2009 for waste sampling and analysis to estimate and convert HHV and LHV [68-69].

$$\mathrm{LHV}\ (\mathrm{MJ}/kg) = \mathrm{HHV}\ (\mathrm{MJ}/kg) - 0.2122H \qquad (2)$$

$$\mathrm{HHV}_w = \frac{1}{m}\sum_{j=1}^{m} HHV_{jd} \times \frac{100 - M}{100} \qquad (3)$$

$$\mathrm{H}_d = \sum_{i=1}^{n}\left[H_{id} \times \frac{C_{id}}{100}\right] \qquad (4)$$

$$\mathrm{LHV}_w = \mathrm{HHV}_w - 24.4 \times \left[M + 9\mathrm{H}_d \times \frac{100 - M}{100}\right] \qquad (5)$$

Where, $\mathrm{HHV}_{jd}$is the higher heating value at dry basis (kJ/kg), HHV_w is the higher heating value at wet basis (kJ/kg), LHV_w is the lower heating value at wet basis (kJ/kg), H_d is the percentage of hydrogen at dry basis, H_{id} is the percentage of hydrogen in a category of waste at dry basis, C_{id} is the content of a category of waste at dry basis (%), *j* is the ordinal

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number of repeated measurements, m is the number of repeated measurements, i is the ordinal number of waste category, n is the number of waste category, 24.4 is the latent heat of water condensation (kJ/kg).

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