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Global knowledge base for municipal solid waste management: Framework development and application in waste generation prediction

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ABSTRACT

Increasing municipal solid waste (MSW) generation has become not only a major sustainability challenge and a considerable financial burden for municipalities across the globe, but also an opportunity to promote a circular economy, provided adequate information is made available. Data and information on MSW generation, characterization, and management practices are prerequisites to studying and optimizing solid waste management systems (SWMS). However, such data and information are usually dispersed, unsystematized, and suffering from various availability and quality issues. This study aims to assemble and provide access to the current landscape of MSW data by establishing a comprehensive framework for understanding the interconnectedness of various subdomains of MSW knowledge. Existing databases and governmental reports were reviewed to compile 1720 records of MSW generation, composition, management practices, and socioeconomic contexts for 219 countries and 410 cities. Multivariate linear regression and additive models were built to relate MSW generation, composition, and recovery rates to demographics, economic development, and climate patterns of cities and regions. These models generate new insights into the complex nature of SWMS and provide an evidence-based decision-making tool to future researchers and policy makers. Specifically, economic development (GDP), density factors (population, population density, and household size), sustainability initiatives, education, and regulation are all identified as positive drivers toward the targets of United Nations Sustainable Development Goal 12.

1. Introduction

With projected population growth and economic development, greater municipal solid waste (MSW) generation is expected (Chen et al., 2020; Kaza et al., 2018). This not only imposes a major sustainability challenge, but also portends a heavy financial burden on municipalities managing these streams across the globe (World Bank, 2019). Historically, municipalities have been predominantly disposing of their MSW streams through landfilling, open-dumping, and incineration without prioritizing on waste valorization or resource recovery (Kaza et al., 2018; World Bank, 2019), a major priority for current environmental policies. However, as societies begin to embrace a circular economy model, solid waste management systems (SWMS) need to be both resilient enough to safely manage increased MSW generation and efficient in maximizing resource recovery, while minimizing environmental impacts and economic costs. The dual SWMS functions of waste disposal and waste valorization echo the U.S. EPA goal of sustainable materials management (U.S. EPA, 2019) and the EU circular economy action plan (COM(2020) 98 final) as important actions toward the United Nations Sustainable Development Goals (UN SDGs) (United Nations, 2015).

This new waste management paradigm requires a holistic approach of optimizing collection logistics, deploying optimal waste treatment and valorization technologies, and mobilizing social and financial capital to achieve the most sustainable recovery and disposal of MSW (Magazzino and Falcone, 2022; Marshall and Farahbakhsh, 2013). In particular, the recent shrinkage of global demand for recyclables

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exacerbated by the China's waste import bans calls for resilient local waste valorization capacity building (Brooks et al., 2018; Li et al., 2021). All of these requirements are predicated upon robust scientific understandings of solid waste management and a rich collection of data on MSW generation, characterization, management practices, and SWMS performance (Chowdhury, 2009). However, due to the historical emphasis on waste disposal and a lack of financial incentives for data collection, MSW managers and decision-makers are faced with sizable data and knowledge gaps (Chowdhury, 2009; Cohen and Gil, 2021; Reike et al., 2018).

Existing MSW data and information come from academic and non-academic sources on a variety of topics. To set the stage for a global knowledge base, we first provide an overview of available data sources, the types of information provided, and accessibility. Most academic studies published in peer-reviewed journals investigate waste characterization (Götze et al., 2016; Karak et al., 2012), predictive models of MSW generation (Beigl et al., 2008; Kolekar et al., 2016), SWMS performance evaluation (Campitelli and Schebek, 2020; Khandelwal et al., 2019), and SWMS optimization (Van Engeland et al., 2020). Non-academic sources, mainly in the format of datasets, databases, and reports from governmental and non-governmental organizations, are the primary data sources for MSW generation, MSW composition, and MSW management practices (Kaza et al., 2018).

Academic MSW characterization studies aim to understand the quality of MSW by characterizing various chemical, physical, and compositional properties of MSW streams. Commonly reported properties include the fractions of MSW (e.g., percentages of plastics, paper, and food waste), heavy metals and toxic elements (Viczek et al., 2020), nutrients concentration, and energy recovery parameters, such as heating values, ash content, halogen concentrations, and volatile matter (Götze et al., 2016). These studies either target one specific MSW stream of high priority, such as organic residues (Campuzano and González-Martínez, 2016; Dou and Toth, 2021), or compare multiple parameters across different MSW fractions for a specific region (Gu et al., 2017).

The total quantity of MSW generation is the most commonly reported metric of system production, typically aggregating over periods of days, months, or years. Researchers have applied several modeling techniques, such as regression analysis, input-output models, time series models, and machine learning models to predict MSW generation (Abdallah et al., 2020; Beigl et al., 2008; Kannangara et al., 2018). Although these models vary in form and scale, they typically compile and organize MSW generation information in the form of either time-series data, cross-sectional data, or panel data, and relate MSW generation to various socioeconomic and demographic variables. These explanatory variables, such as GDP, household size, education, and population, are typically collected by national or state census bureaus or through local primary surveys.

The formulation and evaluation of SWMS performance metrics represent another expansive body of academic research. Thousands of studies have been published since the 1980s to evaluate SWMS in terms of their environmental footprints, societal impacts, economic costs, and governmental interventions (Campitelli and Schebek, 2020; Turcott Cervantes et al., 2018). Most of these studies focus on quantifying the environmental footprints of SWMS using life cycle analysis (LCA) (Campitelli and Schebek, 2020), either relying on the life cycle inventory (LCI) data built into LCA software such as SimaPro, GaBi, EASETECH (Environmental Assessment System for Environmental Technologies), and IWM (Integrated Waste Management), or compiling their own site-specific LCI data (Khandelwal et al., 2019; Laurent et al., 2014b; Ripa et al., 2017).

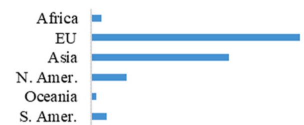
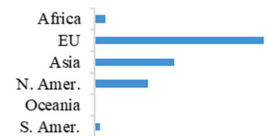
To improve the performance of SWMS, a number of mathematical optimization models have been developed by researchers to support strategic and operational decisions in MSW management (Van Engeland et al., 2020). Most of these models are validated with real-world case studies and incorporate valuable information, such as the capital investments, operation costs, and revenues associated with SWMS (Roberts et al., 2018). In addition, some studies factor in the uncertainties in waste generation, costs, and technology capacity (Van Engeland et al., 2020). Environmental and social impacts such as pollutant emissions and job creation are also acknowledged as important optimization objectives but are less commonly adopted (Van Engeland et al., 2020).

Non-academic sources of MSW data mainly include governmental reports at regional and national levels and reputable NGO databases from the United Nations (UN), World Bank (WB), Eurostat, OECD Stat, etc. These NGOs and governmental agencies are the primary data sources for MSW generation, composition, and management practices since they are typically responsible for either managing MSW or providing data on MSW (Kaza et al., 2018). Although many local waste managers contract with academic institutions or consulting companies to conduct characterization or composition studies for their jurisdictions, they normally support these studies by providing access to primary data on local waste generation through waste collectors or weighing stations.

The aforementioned academic and non-academic sources are summarized in Table 1. The bar charts embedded in the "Geographic Distribution" column represent the relative abundance of studies for each continent. Our review suggests that historically, academic studies were predominantly conducted for the developed countries in the EU and North America. However, recent publication trends indicate a momentum shift towards developing countries in Asia and other parts of the world. Similar shifts have been observed for scientific activities and publications in other disciplines (Tan et al., 2021; Valente de Macedo et al., 2021), reflecting changing prioritization, demand, and capacity for scientific research in these regions. Currently, the overall MSW data landscape is dominated by studies of the EU and Asia (noticeably in China, India, and Iran), followed by North America. Also, it is worth acknowledging the existence of other data sources such as waste technology R&D articles, industry reports, and regional NGO archives. However, due to the relatively low data intensity and sporadicity of these sources, they are not included in this study.

Despite the abundance of MSW data, major issues and knowledge gaps persist. First, existing MSW data are mainly stored in "silos" confined by geographical boundaries or topical focuses (Cohen and Gil, 2021). There is not a single centralized repository to organize all the information in a systemic manner, which is verified by the lack of relevant peer-reviewed articles on multi-attribute MSW knowledge systems (Dias et al., 2021). Second, due to the financial and organizational costs of data collection, waste characterization studies are infrequently conducted or reported, especially in low-income countries (Kaza et al., 2018). This uneven geo-economics distribution of MSW data is also manifested in Table 1. Third, there is a lack of standardization in the definition of MSW and reporting metrics (Bianchini et al., 2011; Wilson, 2015). The main inconsistencies stem from the inclusion of commercial construction and demolition (C&D) wastes, waste tires, and other MSW-like commercial or industrial streams. In addition, discrepancies in MSW quantity reporting are observed in terms of generated MSW, collected MSW, and disposed MSW. Some reports only include residential disposal streams while others include all wastes generated by the public for both disposal and recovery. Fourth, the reliability of MSW data is hard to verify, since governmental reports are normally the only source for such information (Kawai and Tasaki, 2016). For example, a few researchers questioned the reliability of the U.S. MSW generation data reported by the U.S. EPA, claiming that the other assessment method based on facility-level data yielded estimates that were 50% higher due to modeling assumptions, reporting errors, and inconsistent reporting formats (Tonjes and Greene, 2012). Fifth, there is a lack of understanding of MSW management at the municipality level, since most data sources report at an aggregated national or regional level. This is a particularly relevant issue for countries with diverse socioeconomic and demographical conditions, such as India and China, where MSW

Table 1
Overview of the major MSW data sources identified in this study.

Data Sources		Data Types	Geographic Distribution[1]	Selected References
Academic	Waste characterization	heat values, moisture, inert matter, volatile matter, ultimate analysis results, composition		(Götze et al., 2016)* Dou and Toth (2021) Campuzano and González-Martínez (2016) Karak et al. (2012)
	Waste generation prediction	quantity of MSW, various socioeconomic and demographic parameters		(Beigl et al., 2008)* (Kolekar et al., 2016)* Abdallah et al. (2020) Kannangara et al. (2018)
	SWMS performance evaluation	environmental, social, and economic impacts of SWMS		(Campitelli and Schebek, 2020)* (Laurent et al., 2014a, 2014b) Khandelwal et al. (2019)
	SWMS optimization	operation costs, capital investment costs, capacities and efficiencies of technologies		Juul et al. (2013) (Van Engeland et al., 2020)* (Sandoval-Reyes et al., 2022)*
Non-academic	NGO databases/ reports	MSW generation, composition, management practices	UN and WB databases have global coverage, while OECD and Eurostat cover their member countries.	What a Waste Database (World Bank, 2021), (United Nations Statistics Division, 2021), (Eurostat, 2021), (UN-Habitat, 2010), (OECD, n.d.)
	Governmental reports	MSW generation, composition, management practices	Almost all countries have national waste statistics, except 31 countries in the Sub-Saharan Africa region and 8 countries in other regions (Kaza et al., 2018).	Gov. environmental agencies, statistic offices at various levels

Note: 1. The geographical distribution of studies in each academic source is estimated based on data reported in the studies denoted by an asterisk in each row.

management scenarios in rural areas could drastically differ from relatively wealthy, densely populated urban districts (Wang et al., 2017).

This study does not intend to bridge these data gaps; instead, we attempt to reveal the current landscape of MSW data by recognizing these important limitations. Moreover, as a complex socio-technical system, SWMS requires holistic design and decision-making approaches empowered by a systemic view (Marshall and Farahbakhsh, 2013). Thus, we aim to establish a comprehensive MSW knowledge base that indexes major data sources, reveals the interconnections among sub-domains of MSW knowledge, and facilitates knowledge discovery and communication. Recognizing the extensiveness of this undertaking, we choose to focus this paper on the development of a robust knowledge base framework rather than exhaustive data collection. Based on this framework, the interconnections between MSW generation and the socioeconomic context of SMWS are investigated as an illustration of a major intended application of the knowledge base.

2. Methodology

2.1. Framework of the knowledge base

The first step in developing a comprehensive knowledge base is to establish a logical framework to categorize the heterogeneous data sources and to relate the sub-domains of MSW information. The systemic knowledge base framework is built in a similar fashion as in system dynamics models (Rafew and Rafizul, 2021; Xiao et al., 2020), capturing the influences and interconnectedness of individual "siloed" sub-domains.

SWMS-related knowledge can be categorized into three major components: the socioeconomic context of SWMS, the SWMS themselves, and the performance of SWMS. The regional socioeconomic context of SWMS consists of the general public (characterized by its demographics, lifestyles, and education/environmental awareness), regional economy, climate patterns, and governance (Abdallah et al., 2020; Beigl et al., 2008; Dias et al., 2021; Kolekar et al., 2016). The broader socioeconomic context of SWMS includes domestic and international trades, as well as markets for secondary and primary materials (Brooks et al., 2018; Das et al., 2019; Matter et al., 2015). The second component contains the sub-domains related to the MSW management system itself, such as waste types, waste generation, waste properties, technologies (collection, transportation, storage, preprocessing, and final treatment), and MSW management (the deployment and implementation of waste technologies) (Roberts et al., 2018). Municipalities across the globe might share similarities in waste types and waste technologies; while their waste generation, composition, and local SWMS configurations may differ dramatically. The third component is the performance of SWMS in the typical "three pillars of sustainability" fashion: financial impacts (e.g., costs, revenues, and return on investments), environmental impacts (e.g., climate change, environmental quality, biodiversity, and ecosystem health), and societal impacts (e.g., labor condition, job creation, public engagement, and public health) (Aleluia and Ferrão, 2017; Rodrigues et al., 2018).

While most of the sub-domains of MSW knowledge are represented by existing data sources identified in Table 1, the interconnectedness among these sub-domains is rarely studied or reported in a systematic way. The local socioeconomic context, comprising demographics, lifestyle, education, economy, climate, and governance, determines local MSW generation quantity and quality (Johnstone and Labonne, 2004). Combining with the inherent characteristics of different waste types, the local MSW generation determines various physical, chemical, and compositional properties of different MSW streams. It is these waste properties along with MSW generation that suggest technically preferable waste valorization and disposal technologies. When it comes to the local deployment and operations of these technologies, the socioeconomic context plays a determining role again. For example, municipalities may prefer to landfill or incinerate their mixed MSW based on their land availability and public perception. Furthermore, international or cross-region trade policies, such as China's waste import bans, can influence market demand and prices of secondary materials, shifting local MSW management scenarios (Brooks et al., 2018). Finally, based on the technology selection, local implementation, and daily operations, various societal, environmental, and financial performance metrics can be evaluated using life cycle analysis (LCA) and life cycle cost assessment tools (Martinez-Sanchez et al., 2015).

This overarching knowledge base framework not only serves as a checklist for data collection efforts to ensure comprehensiveness, but also functions as a roadmap for identifying and revealing under-investigated interconnections among the sub-domains of SWMS knowledge.

2.2. Data collection and quality control

Data collection focusing on the country-level and city-level MSW generation, composition, management practices, and corresponding socioeconomic contexts was conducted through extensive online searches into state and municipal environmental agency websites in the U.S. and reputable international NGO databases. The scope and key parameters of the knowledge base are detailed in Appendix A1 and the specific data sources and collection processes are provided in Appendix A2.

The primary measure of quality control is the identification of reputable data sources such as the WB, UN Statistics Division (UNSD), Eurostat, OECD Stat, and peer-reviewed journals. Other data quality control measures include source tracing to differentiate primary and secondary sources, prioritizing recently published data to reflect the latest MSW generation trends, and differentiating total MSW generation from disposed MSW to account for the variation in reporting metrics. The knowledge base framework with currently collected data is available at the institutional repository of CMU KiltHub (DOI: 10.1184/R1/20280138) for open access and collaboration.

2.3. Waste prediction modeling

One direct application of the established knowledge base framework is to investigate how socioeconomic context could impact MSW generation and management practices. To predict daily per capita MSW generation, MSW composition, and MSW recovery rate, statistical models are built, including multivariate linear regression (LR) models and multivariate additive models (AMs).

$$Y = \beta_0 + \sum_{j=1}^{p} \beta_j X_j + \varepsilon \tag{LR}$$

$$Y = \beta_0 + \sum_{j=1}^{p} f_j(X_j) + \varepsilon \tag{AM}$$

Where: β_0 to β_p are coefficients, ε is the error term and $f_j(X_j)$ is the unknown smooth fit function from data.

LR has been widely adopted for building econometric models, and for revealing linear relationships between dependent variables and explanatory variables. AMs share similar assumptions of multivariate normality, linear relationship, and independency of observations with LR. However, AMs relax the linearity assumption of LR models by allowing dependent variables to fit to nonlinear terms of explanatory variables (e.g., polynomial terms) (Fang and Chan, 2015; Ravindra et al., 2019). Thus, AMs are capable of modeling both linear and nonlinear relationships between MSW generation and the collected explanatory variables (listed in Table A1).

Specifically, the MSW generation prediction modeling is conducted in several steps (see Fig. 1). After data collection and preparation, exploratory data analysis (EDA) is performed to understand the

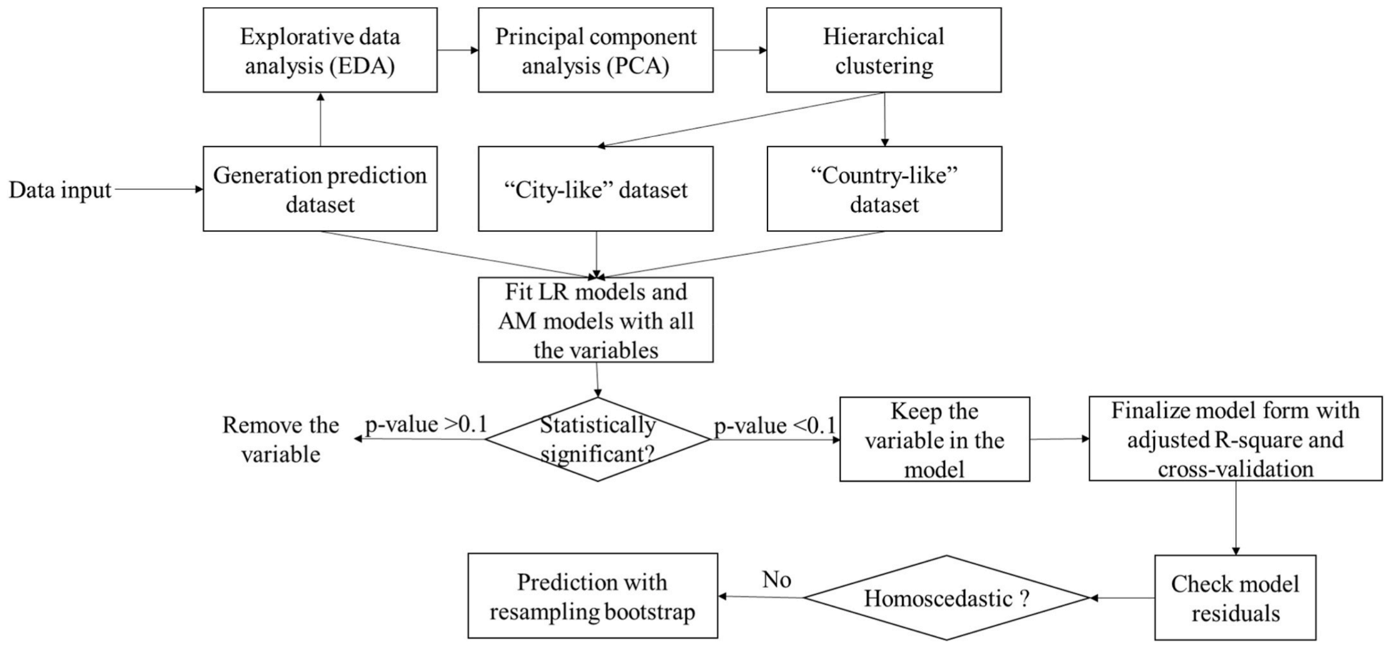


Fig. 1. Flow chart of MSW generation prediction modeling process.

distributions of and the correlations among all the variables. Then, principal components analysis (PCA) and hierarchical clustering analysis are conducted to reduce the dimensionality, complexity, collinearity effects, and heterogeneity of the dataset for better model performance and interpretability.

Next, various AMs and LR models are fitted to predict per capita MSW generation. Adjusted R-square is adopted for penalizing added degrees of freedom when comparing LR models and AMs with different numbers of fitted parameters. Due to the relatively small size of the dataset, the selection of explanatory variables and their degrees of freedom (for the AMs) are determined using 10-fold cross-validation (CV), which randomly splits the entire datasets into 10 data folds of the same size (i.e., 9 training folds, and 1 testing fold). In each CV iteration, an AM model is fitted with the 9 training folds and tested of the mean squared errors (MSEs) on the testing fold. This fitting and testing iteration repeats 10 times with a different fold selected as the testing fold each time to calculate the average MSEs. In addition to adjusted R-square and CV, the maximum degree of freedom for nonlinear terms is capped at 5 in the AMs to further control for overfitting.

The final model forms of the LR models are determined based on the highest adjusted R-squares by removing the explanatory variables that are not statistically significant (p-value >0.1) from the model. AMs are finalized by maximizing adjusted R-squares and minimizing MSEs. Because the built-in prediction confidence intervals (C.I.) of statistics software are calculated based on the homoscedasticity assumption, which may or may not hold, numerical methods are required to simulate the C.I. of our model predictions. To accomplish this, the non-parametric bootstrap technique of resampling training data is applied to quantify prediction uncertainty (Dixon, 2001).

This methodology is also applied to predict MSW composition (paper and food waste fractions) and MSW recovery rates, defined as the percentages of MSW recycled or composted. The R code used to perform all these analyses is provided as Appendix B.

2.4. Outcome evaluation against the UN SDGs

MSW management is extensively related to the UN SDGs (Fatimah et al., 2020; Hannan et al., 2020). After LR models are built for predicting per capita MSW generation (Model 1), food waste fractions (Model 2), and MSW recovery rates (Model 3), Model 1 is multiplied with Model 2 and Model 3, respectively, to estimate total food waste generation (Model 4) and total recovered MSW (Model 5). Model 1, 3, 4, and 5 correspond to the UN SDGs sub-targets of 12.3, 12.4, and 12.5 (United Nations, 2015). To understand the impacts of key socioeconomic variables on these SDGs, the first order derivative of each socioeconomic variable is taken and evaluated at the mean values of all the variables. A positive derivative indicates that the socioeconomic variable is likely a positive driver towards the related SDG targets.

3. Results and discussions

3.1. Mapping of the current MSW data and knowledge landscape

The identified MSW data sources listed in Table 1 are mapped to the knowledge base framework described in Section 2.1 (see Fig. 2). The colored circles in Fig. 2 represent various data sources, with the placement of the circles indicating whether a data source focuses on the interconnections between sub-domains (e.g., SWMS optimization studies) or it provides information on both the interconnections and the individual sub-domains (e.g., waste characterization studies). It is worth mentioning that both SWMS optimization studies and performance evaluation studies assess the environmental and financial impacts of SWMS. However, both types of studies are assigned to just one type of impact category based on their respective emphases. The colored arrows denote the interconnections explored or revealed by existing studies, including the socioeconomic drivers of waste generation, physicochemical properties of different MSW streams, applicability of technologies, and the environmental and financial impacts of different SWMS configurations.

The three major under-investigated interconnections are highlighted with black dashed arrows in Fig. 2. First, waste properties have been primarily characterized based on waste types, with limited or no adjustment to waste quantity and generation behaviors. For example, the compostability of food waste depends not only on the type of waste, but also on the contaminant levels, moisture levels, nutrient ratios, etc. Second, MSW generation is usually reported on the total annual quantity, with insufficient information to break it down into each major waste type. Third, SWMS decisions are predominantly made based on the quantity of MSW and the financial costs of technically feasible technologies. Nevertheless, the real-world SWMS are embedded in

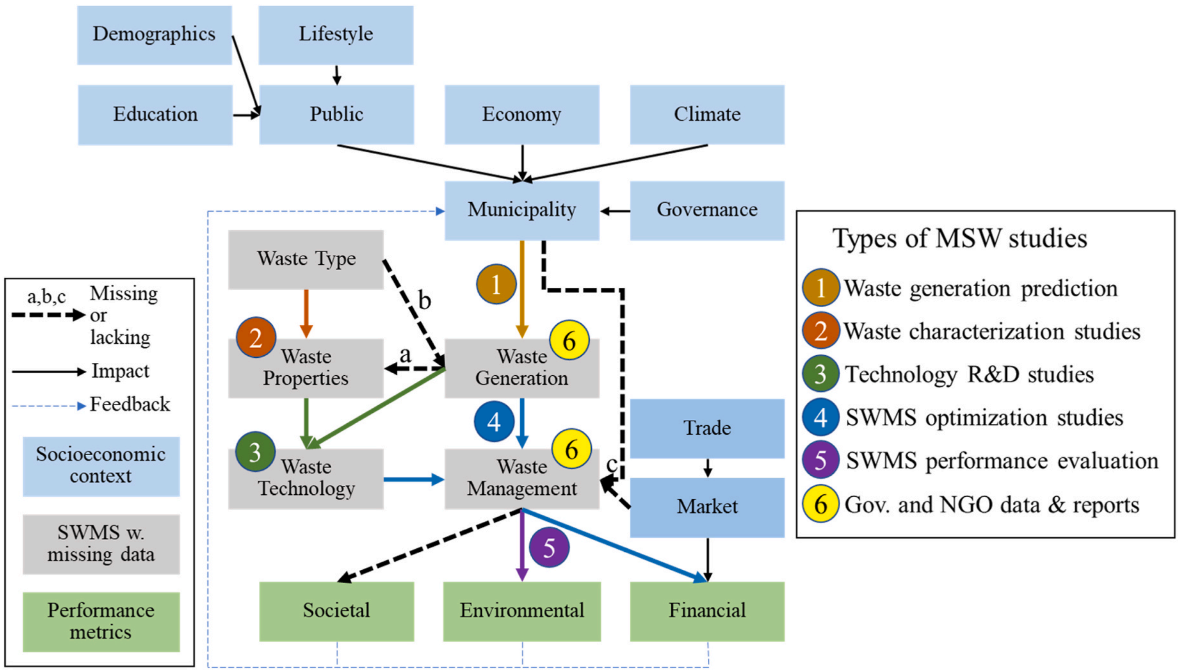


Fig. 2. Overview of the current MSW data landscape. The dotted arrows represent the 3 major under-investigated interconnections among the sub-domains of MSW knowledge. The colored arrows highlight the interconnections investigated by existing data sources (colored circles).

complicated decision-making contexts that include trade policies, market conditions, governance, and consumer behaviors, leading to diverse SWMS configurations (UN-Habitat, 2010). There are increasing numbers of empirical studies on how consumer behaviors impact SWMS (Kaplan Mintz et al., 2019; Meng et al., 2019; Tong et al., 2018). However, such studies have not been systematically integrated into the decision-making process.

Apart from these missing interconnections, there is also a lack of information to effectively characterize and model each sub-domain of SWMS. For example, MSW generation needs to be complemented with waste quality for valorization considerations. Quantity, characterization, and management data need to be enriched for waste types that are not included in this study. As for technologies, most studies focus on traditional options such as landfill, incineration, composting, and mechanical recycling, precluding the promotion of emerging valorization options, such as reuse and remanufacturing. Lastly, local SWMS configurations are seldomly reported in detail, which makes it difficult to evaluate the socioeconomic drivers and policy levers of SWMS in a local context.

3.2. Overview of MSW generation and management

As a result of our targeted data collection effort on MSW generation, composition, management practices, and socioeconomic context, a total of 1720 records (507 city-level records and 1213 country/state-level records) were collected, covering 410 unique cities, 219 countries/territories, and 41 U.S. states. The average per capita MSW generation rate across the database is 1.25 kg/person/day, with a standard deviation of 0.66 kg/person/day. It is worth mentioning that most of these MSW generation records are from developed countries such as the U.S. and most EU countries. Thus, this average value should not be regarded as an estimation of the global average. For the U.S. states and cities, the average MSW generation rate is significantly higher at 2.63 kg/person/day with a standard deviation of 0.72 kg/person/day, while the average

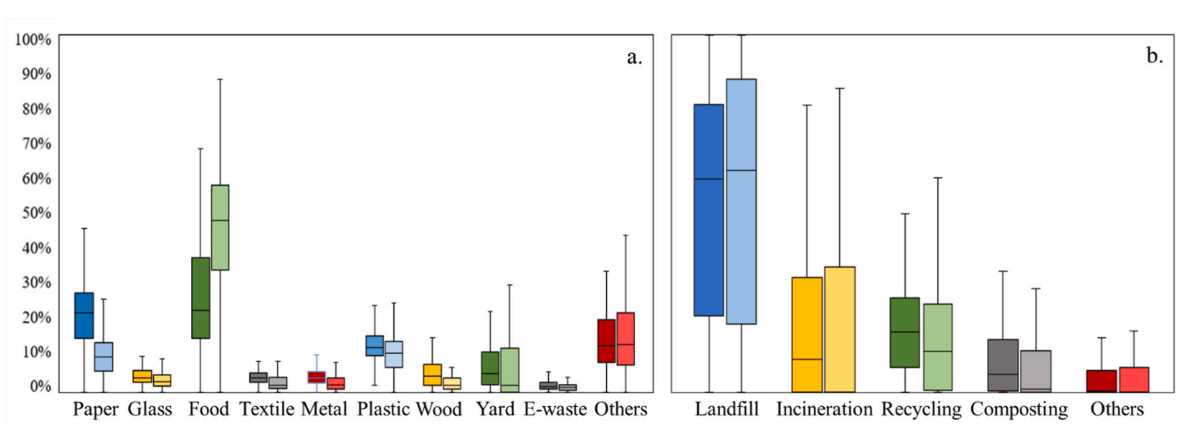


Fig. 3. Comparisons of a) MSW composition and b) MSW management practices (i.e., the percentages of MSW treated by each option). For each MSW type and management option, the darker-colored box plot on the left represents the distribution of high-income countries (based on the WB classification), while the box plot on the right represents the distribution of other countries (low-income and middle-income countries).

MSW disposal rate is 1.83 kg/person/day with a standard deviation of 0.33 kg/person day.

The compositions of MSW streams in high-income countries and other countries are contrasted in Fig. 3a. It is revealed that low-income and middle-income countries tend to generate higher percentages of food waste, while the MSW streams of high-income countries tend to have higher percentages of paper waste. Differences in the distributions of other major waste types (glass, textile, metal, plastic, wood, yard, e-waste, and others) are not statistically significant between high-income countries and other countries, despite slightly higher averages for the high-income countries.

Concerning the MSW management practices, high-income countries and other countries share similar distributions dominated by landfill disposal as illustrated in Fig. 3b. It is also revealed that there is a high degree of variability in management practices among the countries and cities, which cannot be explained by the income classification alone.

3.3. Results of waste generation prediction

AMs and LR models were built to shed light on the factors that contribute to the variability observed in MSW generation. Multivariate LR models were built for their superior interpretability, while AMs were developed for capturing nonlinearity and their superior predictive power. After data preparation, PCA, and clustering analysis (detailed results are provided in Appendix A2 and A3), a dataset with 554 "city-like" samples and 1039 "country-like" samples was prepared for regression analysis. Eight explanatory variables (*Population*, *Population Density*, *Household Size*, *Energy*, *GDP*, *Education*, *Sustainability*, and *Unemployment*) were logarithmically transformed for meeting the multivariate normality assumption. The statistically significant fitted coefficients of the linear terms are summarized in Table 2, while the responses of per capita MSW generation to the nonlinear terms in the AMs are visualized in Fig. 4.

Comparing the two model forms, the AMs consistently out-perform the LR models in terms of goodness-of-fit with significantly higher adjusted R-squares. The AMs also yield lower MSEs than the LR models during the cross-validation trials for model selection. However, the differences in MSEs are not always statistically significant, indicating that the AMs are likely, but not guaranteed, to have lower prediction errors than the LR models. Due to the added nonlinear terms of "*GDP*", "*Population Density*", and "*Household Size*", which could undermine the contributions from other variables, coefficients are always slightly different between the AMs and LR models. Overall, model results are robust to model forms, since the coefficients of most explanatory variables share the same positive or negative signs and relatively similar values.

The city-level models have relatively poor goodness-of-fit, mainly because some of the explanatory variables are not available for all the cities, and thus were substituted with their country-level counterparts as proxies. At the city-level, per capita MSW generation is positively associated with local economy, with a significant and positive coefficient of 0.263 for "*GDP*" in the LR model. This positive association is further verified with the smooth fit curve of the AM (see Fig. 4 a.2), which depicts an overall monotonic growth trend with 2 minutes stabilization ranges. Age distribution turns out to be another significant factor, with negative coefficients suggesting that aging societies with higher percentages of population over 65 tend to have lower MSW generation rates (Kannangara et al., 2018). Surprisingly, "*Household Size*" is not statistically significant in the LR model, which can be explained by the AM fitting in Fig. 4 a.1. Due to the bell-shape curvatures, the overall response of per capita MSW generation to "*Household Size*" cannot be captured by a statistically significant (non-zero) coefficient. The interaction between "*Energy*" and "*Education*" suggests that the MSW generation curbing effect of "*Education*" can be undermined by

Table 2
Summary of the regression analysis results of per capita MSW generation prediction.

	City-like Data		Country-like Data		All Data	
	LR	AM	LR	AM	LR	AM
Precipitation_f				−0.196**		
Precipitation_m	−0.337*				−0.248**	
Precipitation_T	−0.940***	−0.582***			−1.057***	−0.455***
Precipitation_s		0.222′				0.139*
Precipitation_w			−0.204*	−0.201**	−0.231**	−0.123*
Temperature_h	−0.323*				−0.146′	
Temperature_E		−0.582***				−0.455***
Temperature_Dc			−0.605***	−0.796***	−0.606***	−0.634***
Temperature_Db	−0.331*	−0.453**	−0.152*	−0.229**	−0.278*	−0.331***
Temperature_Ca					−0.093′	−0.146**
Temperature_Cb	−0.212*	−0.306**		−0.207***	−0.198***	−0.300***
Population			−0.049***	−0.036***	−0.031***	−0.033***
Household Size		**(5)*****	−0.959***	**(4)*****	−0.573***	**(5)*****
Population Density				**(2)*****		**(5)*****
GDP	0.263***	**(5)*****	0.234***	**(5)*****	0.163***	**(5)*****
Service				0.004*	0.006**	0.006**
Energy	0.207**	0.150′	0.295***	0.270***	0.303***	0.203***
Trash Only	−0.491**	−0.738***	−0.340***	−0.520***	−0.395***	−0.536***
Expense	0.010***	0.007**	0.011***	0.007***	0.008***	0.007***
Sustainability	−0.759′		−0.866**	−0.604*		
Unemployment	−0.079′	−0.099*	−0.052*	−0.038′	−0.075***	−0.063**
Age (15–64)	0.017*	0.019*	−0.013**			0.008*
Age (65+)	−0.024**	−0.056***	−0.039***	−0.039***	−0.035***	−0.041***
Education	−1.622***	−1.084*	−1.319***	−0.930***	−1.663***	−0.943***
*Education*Energy*	0.317***	0.280***	0.220***	0.179***	0.301***	0.216***
Adjusted R^2	*0.435*	*0.489*	*0.614*	*0.684*	*0.509*	*0.553*
MSE	*0.379*	*0.346*	*0.118*	*0.098*	*0.216*	*0.193*

Note: significance codes for the p-values of the estimated coefficients: ≤0.001 '***', ≤0.01 '**', ≤0.05 '*', ≤0.1 ''
The degrees of freedom for nonlinear variables in AMs are presented in round brackets.
Precipitation and temperature patterns are expressed with categorical variables of "Precipitation_code" and "Temperature_code", where "code" letters are based on Köppen-Geiger climate classification.
"Trash Only" is a binary variable that denotes if an MSW generation record includes only disposal streams ("Yes") instead of the total generated MSW ("No").

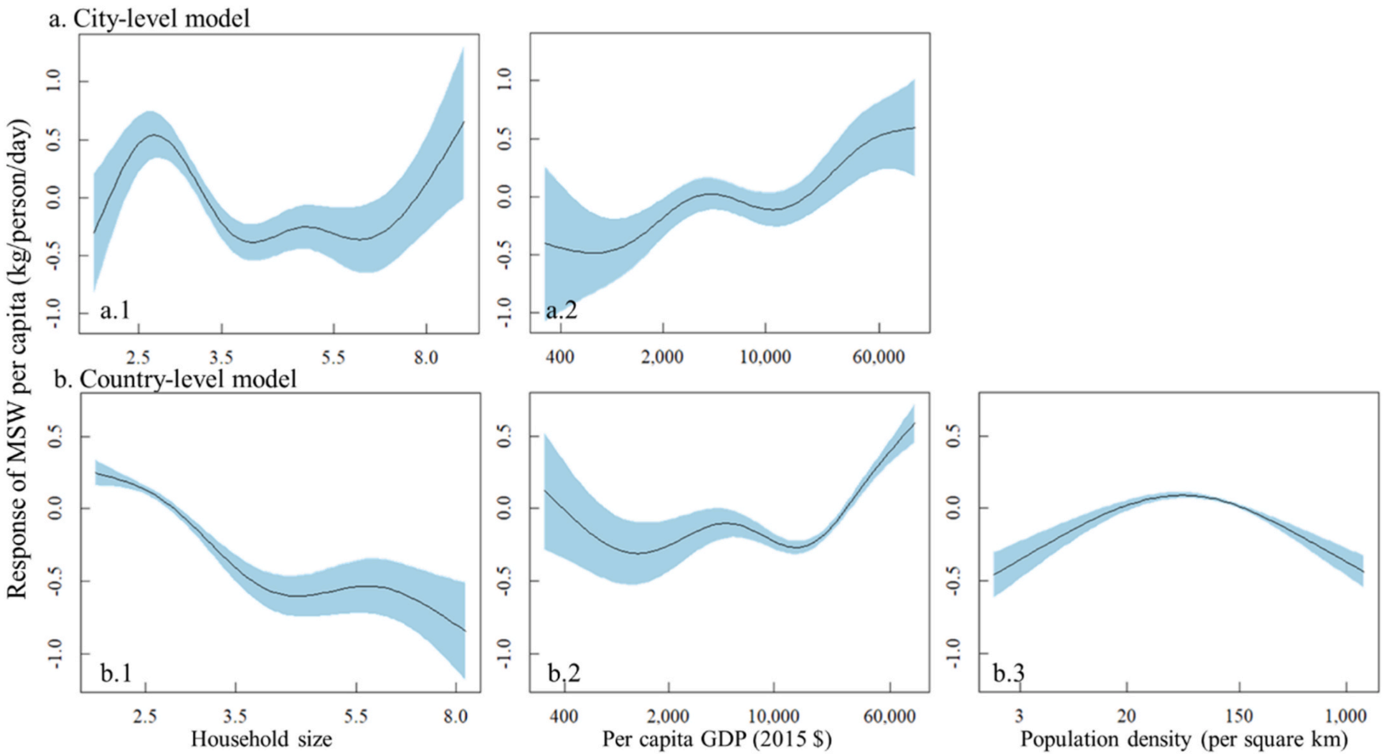


Fig. 4. Responses of per capita MSW generation to the nonlinear terms in the AMs. The response curves are generated by varying the selected nonlinear term (x-axis) while fixing all the other variables in the AM at their mean values. The blue shaded areas represent 95% confidence intervals.

high energy consumption lifestyles. The significant coefficients of the precipitation and temperature patterns suggest that people living in warmer cities are likely to generate more MSW than those living in cooler areas.

The country-level models have adjusted R-squares of 0.61–0.68, which are much higher than those of the city-level models and those reported in previous studies (Beigl et al., 2008; Kannangara et al., 2018). The results suggest that climate patterns, economy, lifestyle, and demographics are all significant factors in predicting the per capita MSW generation. Interestingly, "*Energy*" and "*Expense*", both of which are highly correlated with "*GDP*", yield statistically significant positive coefficients after controlling for per capita GDP. This verifies that extravagant lifestyles (excessive consumption behaviors) are positively associated with higher MSW generation. At the country-level, MSW generation is strongly associated with "*Population*" and "*Population Density*". Countries with a bigger population and either a low or a high population density tend to have lower per capita MSW generation rates. This non-monotonic response of per capita MSW generation to "*Population Density*" (see Fig. 4 b.3) might be due to potential private disposal or low MSW collection coverages in the countries with low population density and high disposal costs for the densely populated countries. In addition, "*Sustainability*", which measures countries' dedication to sustainability initiatives, becomes a significant factor to MSW generation reduction as well. In terms of climate patterns, it is indicated that countries in cooler and dryer climate zones are likely to generate less MSW.

Unlike the city-level AM, the response of MSW generation to "*Household Size*" at the country level features a monotonic decrease when the household size is below 4, followed by a relatively flat stabilization trend. Based on the narrower uncertainty band and the representativeness of data, we believe that the country-level model tells a more credible story that per capita MSW generation decreases as households get larger. This might be attributed to the efficiency gains of bigger households (e.g., purchase in bulk, shared resource utilization, less packaging, etc.) that diminish when the household size is above a certain threshold.

The country-level AM reveals a slight downward trend when the "*GDP*" is lower than 1000 USD/person (see Fig. 4 b.2). There are a few possible explanations for this counterintuitive outcome, which implies an inverse Kuznets curve (Ercolano et al., 2018). First, the smooth fitting of "*GDP*" is able to capture external factors that are correlated with the added nonlinear terms of "*GDP*". It is possible for low-income countries to have weaker sustainability initiatives, which leads to higher MSW generation. This hypothetical explanation is supported by the change in the coefficient of "*Sustainability*" from −0.87 to −0.60, suggesting that part of the contribution of "*Sustainability*" is transferred to the smooth fit of "*GDP*". Second, it is possible that low-income countries have less robust waste collection and data reporting mechanisms, which leads to higher uncertainty and lower credibility in their MSW data (Kawai and Tasaki, 2016). Third, it is possible that the relatively primitive and simple SWMS in low-income countries reduce the effects of under-reporting observed from more complicated SWMS (Powell and Chertow, 2019; Tonjes and Greene, 2012).

The overall models built upon all the data samples can be treated as a direct merge of the city-level models with the country-level models. Although it is advisable to use separate models to predict MSW generation, the overall models can help cancel out "noises" in the data and draw generalized conclusions:

- Population growth is negatively associated with per capita MSW generation.
- Larger household size is generally associated with lower per capita MSW generation. However, this negative correlation becomes weak for households larger than a certain size.
- People living in cooler and dryer regions tend to generate less MSW.
- GDP growth is generally associated with higher MSW generation, and so are extravagant lifestyles (higher energy consumption and higher expenses).

- Societies with a high level of education, aggressive sustainability initiatives, and an aging population are more likely to generate less MSW.

Finally, the MSW generation model was validated with the real-world data of Portugal, which reports an MSW generation rate of 1.40 kg/person/day in 2020 (Eurostat, 2021). Our country-level LR model yields a slightly lower prediction of 1.37 kg/person day with a 95% pivotal C.I. of 1.31–1.43 kg/person/day. The observed value, which is just 2% higher than our model prediction, falls well within the prediction C.I. (see Figure A.5 in Appendix A.3). It should be noted that the model prediction accuracy, as well as the goodness-of-fit, is heavily influenced by the global nature of the dataset and the heterogeneity not captured by the model. Thus, to achieve higher prediction accuracy, building customized versions of these models on regional datasets or observations similar to the object of interest is highly recommended.

Compared to other similar regression analyses, our models explain more variations in the MSW generation thanks to a comprehensive list of explanatory variables. Compared to the machine learning models (Kannangara et al., 2018), which are able to achieve much higher adjusted R-squares due to unjustified model complexity, our models are more interpretable and can be used in a more direct manner to quantify uncertainties in the model parameters and predictions.

3.4. Results of waste composition and recovery prediction

In addition to predicting per capita MSW generation, the same methodology was applied to model MSW composition and MSW recovery as exploratory attempts to reveal the missing interconnections b and c shown in Fig. 2 and discussed in Section 3.1. For MSW composition, only paper fraction and food waste fraction were modeled. Detailed results and discussions are provided in Appendix A.4 and key findings are summarized below:

a) Paper fraction in the MSW can be estimated with models including household size, climate patterns, per capita GDP, energy consumption, service industry GDP, and age distribution. The models capture a good portion of the variance in the paper fraction with adjusted R-squares ranging from 0.56 (LR) to 0.58 (AM). The largest paper fraction is expected at intermediate household sizes with high per capita GDP.
b) The models of food fraction prediction built on a similar group of explanatory variables also exhibit an intermediate goodness-of-fit with somewhat lower adjusted R-squares of 0.44 (LR) and 0.49 (AM). "*Sustainability*" replaces "*GDP*" as the wealth factor, which exhibits a downward turn of food waste fraction at high-income levels.
c) The models for MSW recovery rate similarly exhibit intermediate values of adjusted R-square (0.46 for the LR model and 0.58 for the AM). Our models suggest that societies with higher per capita GDP, aging population, higher population density, and higher degrees of education tend to have higher MSW recovery rates. Existence of waste regulation is also a significant factor, supporting the general efficacy of waste regulations in boosting MSW recovery.

3.5. Implications to the UN SDGs

Sustainable MSW management contributes to various UN SDGs, including SDG 3 (good health and wellbeing), SDG 6 (clean water and sanitation), SDG 8 (decent work and economic growth), SDG 12 (responsible consumption and production), and SDG 13 (climate action) (Fatimah et al., 2020). In particular, our waste prediction models can shed light on 3 specific targets of SGD 12, including: 12.3 "halve per capita global food waste at the retail and consumer levels", 12.4 "environmentally sound management of chemicals and all wastes" (assuming recovery has lower environmental impacts than disposal) (Zaman, 2016), and 12.5 "reduce waste generation through prevention, reduction, recycling and reuse" (United Nations, 2015). The key socioeconomic drivers that contribute to these targets are summarized in Table 3 below.

Table 3
Summary of key socioeconomic and demographic drivers of SDG 12.

SGD target	Model output	Calculation	Drivers +	Drivers −
12.5 Waste reduction	Reduction in MSW generation	Per capita MSW generation (Model 1)	Density Education Sustainability	GDP High-consumption lifestyle
12.3 Food waste reduction	Reduction in food waste	MSW generation * Food waste fraction (Model 4)	GDP (high income) Density Education Sustainability	GDP (mid to low income)
12.4 Environmentally sound	MSW recovery rate	MSW recovery rate (Model 3)	GDP Density Elderly population Regulation	
12.5 Waste recovery	Amount of recovered MSW	MSW generation * MSW recovery rate (Model 5)	GDP Density Regulation High-consumption lifestyle	Elderly population Sustainability

There is a mixture of synergies and conflicts between economic development, as measured by per capita GDP, and achieving SDG 12. As a result of continued pursuit of SDG 8 (economic growth), wealthy societies are likely to achieve the goals of food waste reduction and lower environmental impacts through higher recovery rates. In some cases, MSW generation may increase, but be offset by larger amounts of recovered MSW. These patterns hold true for low-income societies as they pursue SDG 1 (poverty alleviation), except that food waste generation will likely grow as GDP increases, indicating further conflict between SDG 1 and SDG 12 at low levels of economic development. Policy makers should be particularly aware of this issue to ensure the important agendas of poverty alleviation and economic growth does not impede the pursuit of SDG 12.

Density factors (population density, household size, and population), which are likely to be strengthened by SDG 11 (sustainable cities), are revealed to be beneficial to all 3 sub-targets of SDG 12, indicting clear synergies between these two SDGs. Moreover, sustainability initiatives, education, and regulation, which could be driven by SDG 4 (quality education) and SDG 13 (combat climate change), are all identified to be significant and positive drivers to achieving SDG 12 targets.

3.6. Potential applications, limitations, and future work

The main intended application of this knowledge base is to synthesize and systematize MSW knowledge by revealing the relationships among the interconnected sub-domains identified in Fig. 2. As an illustration, statistical models were built to reveal the association between socioeconomic contexts and MSW generation. In addition, this knowledge base can serve as a central repository of MSW data and information with indexing to other related sources, thereby facilitating quicker access and use of broader, more consistent information. This kind of data repository can be adapted by governments at different levels as a foundation for building localized MSW information management systems, which can help reduce data collection barriers, model complexity, and prediction errors introduced by the data variability and sample heterogeneity across the global knowledge base.

Another important area of application is SWMS knowledge discovery and decision support. With a systemic view of existing MSW data and knowledge, researchers and decision makers are empowered to identify and fill knowledge gaps, leverage socioeconomic drivers to achieve UN

SDGs, and optimize SWMS models by combining data-driven approaches with science-based knowledge. For instance, despite the incomplete sufficiency of our models for explaining the underlying reasons for the observed coefficients and curves in Section 3.3, they do provide directions for further model development and data collection to achieve the resolution and power needed to shed light upon the complex interrelationships among technical, economic, social, and behavioral forces that shape SWMS.

There are several limitations in our current work. First, just like the other studies, our MSW generation prediction models inevitably suffer from the "curse of dimensionality" issue. The relatively low-to-intermediate adjusted R-squares suggest that MSW generation is associated with a wide spectrum of socioeconomic variables, which requires an exponentially large collection of data for uncertainty control. Second, our data collection is not exhaustive, and our knowledge base is limited in scope with only major types of MSW included at this moment. Third, with missing observed data, inconsistent metrics, and relatively large uncertainty ranges, our knowledge base also suffers from lingering data quality and availability issues.

Although there is no easy solution to these limitations, actions and research are needed to pave the way to a more sustainable MSW management future. Instead of passively waiting for favorable business cases for MSW data collection, waste managers and practitioners should harness the data collection potential of the Internet of Things (IoT) presented by various smart devices and sensor technologies (Sharma et al., 2020). These technologies can not only generate a massive amount of data automatically at relatively low costs, but also improve data reliability, traceability, transparency, and overall quality. This data collection potential could incubate MSW knowledge bases that are locally deployed, regionally integrated, and nationally connected. Meanwhile, academic communities should leverage the existing data and scientific understandings of SWMS to develop innovative hybrid models, in which data gaps and knowledge gaps can be bridged by existing knowledge and data, respectively. For example, attempts to predict waste fractions using data-driven approaches might have a higher chance of success with better scientific understandings of the correlated variables or the mechanistic material flows of these MSW streams.

The sustainable future of MSW management hinges on systematic and streamlined collecting of MSW data, and subsequent translation of these data into insights and decisions. This study provides a solid base for integrating these two crucial aspects into a single integrated framework. Future improvements should focus on extensive data collection, scope expansion to include other non-hazardous wastes, modeling of the under-investigated interconnections, and local deployment and application of the knowledge base.

CRediT authorship contribution statement

Rui He: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft. **Mexitli Sandoval-Reyes:** Data curation, Formal analysis, Writing – review & editing. **Ian Scott:** Data curation, Formal analysis, Writing – review & editing. **Rui Semeano:** Data curation, Formal analysis, Writing – review & editing. **Paulo Ferrão:** Supervision, Funding acquisition, Writing – review & editing. **Scott Matthews:** Supervision, Writing – review & editing. **Mitchell J. Small:** Supervision, Writing – review & editing.

Declaration of competing interest

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

Data availability

I have shared the link to my data

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2022.134501.

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