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Quantification of social metrics for use in optimization: An application to solid waste management

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ABSTRACT

Solid waste management (SWM) is an interdisciplinary field which requires a range of metrics to make informed decisions. Social indicators are of high interest to decision-makers but are particularly difficult to integrate into optimization frameworks, largely due to challenges of quantification. This study presents a methodology for quantifying a social metric for integration into sustainability assessment of solid waste management (SWM) systems using optimization. To identify social indicators, waste managers were consulted in Columbia, Missouri, USA. Meetings were held prior to indicator creation and reviewed mid-project with stakeholders. A number of concerns that could be categorized as social were raised. For the two most pressing issues to managers, quantitative metrics were created. First, SWM experiences high employee turnover, largely due to low wages. Turnover leads to less efficiency in collection and treatment, gaps in service, and cost to citizens. Hence, the first social metric proposed represents turnover of employees including loss of productivity, hiring and replacement costs, and quit rate. Second, this work estimated the value of exposure risk associated with manual material handling activities. This second social metric considered a worker's physical exposure to risk via activities of lifting, carrying, placing, emptying, and sitting. These social metrics were used within a multi-criterion decision-making framework for SWM, extending the traditional focus on economic and environmental objective functions. Results illustrate the trade-offs among these conflicting criteria and provide managerial insights into the costs and benefits of different waste management strategies.

Abbreviations

SWM	Solid Waste Management	MMH	Manual Material Handling
WM	Waste Management	WPE	Worker's Physical Exposure
LCA	Life Cycle Assessment	WMSDs	Work-related musculoskeletal disorders
SWOLF	Solid Waste Optimization Life Cycle Framework	VLI	Variable Lifting Index
DALY	Disability Adjusted Life Years	REBA	Rapid Entire Body Assessment
S-LCC	Societal Lifecycle Costing	RULA	Rapid Upper Limb Assessment
GWP	Global Warming Potential	WBV	Whole-body Vibration
LCIA	Life Cyle Impact Assessment	MSD	Musculoskeletal Disorders
LF	Landfill	ISO	International Standard Organization
MRF	Material Recovery Facility	GHG	Greenhouse Gas
AD	Anaerobic Digestion	OSHA	Occupational Safety and Health Administration
WTE	Waste to Energy	S-LCA	Social Life Cycle Asssessment
		UNEP	United Nations Environment Program

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1. Introduction

Solid Waste Management (SWM) generation has grown proportionally with increasing global population. This growing generation rate demands businesses and public-sector entities collect, treat, and dispose of SWM efficiently (Kovačić et al., 2017). This requires making tailored decisions for SWM strategies with many variables, time lags, and uncertainties. There is a robust academic literature applying optimization models to address SWM issues (Achillas et al., 2013; Goulart Coelho et al., 2017; Singh, 2019) with increasing desire for inclusion of the social impacts and benefits, in addition to the economic and environmental pillars of sustainability (Gutierrez-Lopez et al., 2023). The integration of economic, environmental and social considerations presents a multi-criteria decision making problem for managers to identify sustainable practices that generate the greatest mix of benefits (Rodríguez-Espíndola et al., 2022). However, inclusion of social dimensions of sustainabiltiy remains under-represented.

Previous studies have focused on design phases of SWM systems and define social costs and risks based on their potential impact on customers (i.e., users of the WM service). One common approach has been to use externality costs to characterize the social effects of an SWM system. Cucchiella et al. (2014) used the term “wealth public benefit” to capture the effect on public health from the use of an incinerator. Similarly, Mavrotas et al. (2015) implemented external costs to represent impacts to the environment and the quality of life. Other researchers have defined these concepts in terms of risks such as describing societal risk through possible fatalities due to a WM system implementation (Santibañez-Aguilar et al., 2015) and visual-contamination due to emissions (i.e. CO_2, SO_2, NO_x, heavy metals, and volatile organic carbon molecules) which impair citizens in nearby areas (Yousefloo and Babazadeh, 2020). Externality costs and risks, although widely used, struggle with the internalization process, i.e., incorporating the parties involved into the decision-making process (Fianu, 2017).

Life Cycle Assessment (LCA)-based optimization has been applied to environmental impacts of SWM systems, although applications to social sustainability have been more limited. Levis et al. (2013) presented a modeling approach (SWOLF, the Solid Waste Optimization Life Cycle Framework), to more accurately represent SWM systems that consider many different waste streams, varying generation sector types (e.g., single family collection), and multiple potential collection and treatment processes. However, SWOLF and other similar optimization frameworks have incorporated costs and environmental criteria into analyses of SWM, without inclusion of social criteria (Habibi et al., 2017). Limited attention has been placed on optimization approaches that incorporate the three pillars of sustainability together (Gutierrez-Lopez et al., 2023), hence, a need for further research in this area exists, particularly with respect to the quantification of social costs and benefits. Minimal consideration has been given to the definition of social metrics that can be used in an operational WM system using input from both decision makers and literature.

This study departs from previous work in that it narrows the range of concerns not from literature but by using details from a case site obtained by speaking with the managers directly involved with the waste management operations. Using data from the field to shape the metrics yields a more socially robust analysis best suited for decision making. This work elaborates on further alternatives to quantify such impacts of SWM activities on employees.

This paper first provides a new approach for the quantification of stakeholder-identified social concerns within a local WM system, then introduces these metrics into an optimization framework to provide insights into the interactions between the conflicting criteria associated with WM systems. This is achieved via an extension of SWOLF to include social criteria. Social components are defined based on the needs of a local WM system, in Columbia, Missouri, USA. These social components are employee turnover and the related factor of a worker’s physical exposure to activities such as lifting, carrying, placing, emptying, and sitting. The grounds for the selection of these components are detailed in Section 4.2.

These two new social criteria are utilized for both single objective optimization minimizing social costs, and to perform a multi-criteria analysis, identifying trade-offs between social, economic and environmental criteria. Consequently, Section 2 summarizes the previous research and applications of social criteria in SWM optimization in the literature. Section 3 introduces the case study used in this article. Section 4 provides explanations of the adaptation of SWOLF to consider social metrics and elaborates on their quantification. Section 5 presents the results and discussion derived from the case study and sensitivity analysis. Finally, Section 6 states the conclusions and identifies possible directions for future research.

2. Literature review

2.1. Social criteria and optimization

Mathematical programming has been widely used to address SWM problems, with many authors considering multiple objectives. A comprehensive review presented by Gutierrez-Lopez et al. (2023) discussed studies from the past decade emphasizing the inclusion of social aspects and the challenges of their quantification for optimization purposes. Applications vary from general SWM networks design to more specific optimization of WM treatment processes. Sustainable WM systems frameworks include the interests of multidisciplinary stakeholders such as manufacturers, managers, local governments, customers, technical and legislative experts, among others (Chowdhury et al., 2023). To understand these social system factors, researchers use a variety of methods such as interviews, surveys, or questionnares to learn from different stakeholders (Table 1). According to the findings presented by Gutierrez-Lopez et al. (2023), only 10% (N = 125) of the authors involved stakeholders to define social indicators with decision-making purposes.

Previous multi-criteria optimization studies have considered social concerns in SWM that can be associated with different stakeholder groups identified in United Nations Environment Program (UNEP) guidelines for Social Life Cycle Assessment (S-LCA) (Benoît and Mazijn, 2013). Table 2 summarizes the social concerns included in prior optimization studies (please see the Stakeholder groups identified in the bottom row), we observe that the previous literature has focused on the Local Community (all 19 studies included in Table 2), with other stakeholder groups addressed in many, but not all of these studies, such as Workers (10 studies), Consumers (13 studies), Society (12 studies) and Value Chain Actors (including SWM management, 12 studies), although none of the studies specifically addressed Children. The most popular social metric modeled was Job Creation which presents a straightforward definition to measure the number of job opportunities due to the SWM decisions made (e.g., establishing new treatment facilities) (De Feo et al., 2021; Deus et al., 2019; Heidari et al., 2019;

Table 1
Methods to understand social factors from stakeholders.

Methods	Social aspects	Authors
Questionnaire-based assessment	Determinants of sustainability: social, institutional, and economic elements	Zurbrügg et al. (2012)
Structured questionnarie	Attitudes of residents related to life cycle of facilities	Al-Khatib et al. (2014)
Social surveys	Social awareness about WM	Ferronato et al. (2017)
Fuzzy delphi method	Evaluation of WM technology alternatives	Govind Kharat et al. (2019)
Fuzzy simple additive weighting	Opinion of experts of social performenace of WM technologies	Rabbani et al. (2021)
S-LCA	Social inventory indicators that affects workers, local community, and society.	Ardolino et al. (2023)

Table 2
List of social concerns found in literature applying optimization techniques to solid waste management systems.

Author	Social concerns														
	Visual pollution	Public acceptance	Social acceptance	Social satisfaction	Public Participation	Health and safety	Job creation	Risk	Coverage rate	Collection time	Facility distance	Land occupation	Quality of products	Credibility & Transparency	Institutional acceptance
Zurbrügg et al. (2012)			✓						✓						✓
Al-Khatib et al. (2014)										✓				✓	
Milutinović et al. (2016)			✓								✓		✓		
Ma and Hipel (2016)					✓										
Taweesan et al. (2017)				✓											
Ferronato et al. (2017)					✓					✓				✓	
Habibi et al. (2017)	✓														
Govind Kharat et al. (2019)		✓				✓									
Heidari et al. (2019)							✓								
Deus et al. (2019)					✓	✓	✓		✓					✓	✓
Fernández-Braña et al. (2019)				✓					✓						
Palafox-Alcantar et al. (2020)				✓			✓								
Jucá et al. (2020)									✓						
Mamashli and Javadian (2021)						✓	✓	✓							
Xu et al. (2021)							✓								
Rabbani et al. (2021)			✓			✓	✓			✓	✓	✓	✓		
De Feo et al. (2021)						✓	✓								
Mahdavi et al. (2022)					✓	✓	✓								
Tirkolaee et al. (2024)							✓								
Stakeholder group[a]	Local community	Consumer Value chain actors Local community				Worker Local community	Workers Local community Society		Consumer Local community			Local community Society	Consumer Value chain actors	Value chain actors Local community Society	

[a] Stakeholder group based on UNEP guidelines for S-LCA (Benoît et al., 2013).

Mamashli and Javadian, 2021). Other common social impact metrics found in the literature were related to Health and Safety, such as estimating damage to human health using the concept of disability adjusted life years (DALY) (De Feo et al., 2021); lost days caused by work injuries (Mamashli and Javadian, 2021), effect that treatment centers might have to employees health using a scoring system (Govind Kharat et al., 2019; Rabbani et al., 2021), or risk based on population location (Mamashli and Javadian, 2021).

LCA has been used to assess environmental impacts and resources in waste management systems (Christensen et al., 2020; Fei et al., 2022; Gonzalez-Garcia et al., 2018). By extending the consideration to social themes, S-LCA aims to capture social impacts over the supply chain, and in some cases into future generations of the system under analysis (Ardolino et al., 2023; Mahdavi et al., 2022). The range of possible metrics required to capture all potential health and safety concerns poses a challenge to developing a natural quantification method. S-LCA as a standalone process lacks the capability and role to directly guide-decision-making, since it does not provide prescriptive analysis. In order to provide solutions that incorporate stakeholder perspectives that reflect their experiences, LCA-based methods can be integrated with disciplines such as operations research, through techniques such as multi-criteria decision-making. Thus, in this paper we suggest the application of a collaborative process involving stakeholders to develop a social metric integrated within a mathematical optimization framework.

2.2. Life-cycle based optimization using SWOLF

The SWOLF mathematical optimization framework provides a decision support tool that accounts for costs and environmental aspects related to SWM. SWOLF utilizes a life cycle-based approach for quantifying environmental impacts and for populating a database of cost components for generic SWM systems. Therefore, it provides adaptability and flexibility accommodating diverse constraints and goals.

SWOLF was introduced by Levis et al. (2013) as a life cycle-based framework to optimize – over multiple time stages – the collection and treatment of all waste materials from curb to final disposal by minimizing cost or environmental impacts. The foreground emissions are calculated using engineering equations and the background emissions, e.g., electricity, diesel, associated with inputs to the SWM system are estimated using data from Ecoinvent v3.5. SWOLF allows a user to adjust key process parameter values to represent local technology or management conditions, (e.g., landfill moisture) and waste diversion constraints. In 2022, Sardarmehni et al. (2022) adapted SWOLF into an open-source Python package called SwolfPy that allows users to create and analyze SWM networks. For illustration purposes, Fig. 1 shows an abbreviated structure of the SwolfPy package with the main elements utilized in this manuscript (see Sardarmehni et al., 2022).

Its adaptability and flexibility has allowed the development of several applications, accordingly, Levis et al. (2014) and other authors have employed SWOLF in case studies using hypothetical or real data, and have developed extensions to the modeling framework. To our knowledge, only one author attempted to integrate a social metric into SWOLF for analysis. Martinez-Sanchez et al. (2017) developed a case study to integrate social costs using S-LCC (societal lifecycle costing), which is defined as accounting prices to represent the marginal damage of externalities caused by pollutants (e.g., CO_2. NO_x, etc.) associated with each treatment option (e.g., incineration, composting) and added to the budget costs. Martinez-Sanchez et al. (2017) excluded other social impacts (such as odor, noise, visual instruction, congestion, etc.) due to a lack of representative data.

SWOLF has been used to evaluate policies in a few instances. Levis et al. (2014) presented the first SWOLF application, analyzing a hypothetical suburban U.S. city over 30 years considering changes in population waste generation, energy mix and costs. Stanisavljevic et al. (2017) used SWOLF to evaluate scenarios that meet EU goals by 2030 in terms of biodegradable materials diversion and recycled materials. Jaunich et al. (2019) evaluated costs and environmental implications of SWM policies for Wake County, North Carolina, showing the potential of waste-to-energy technologies to increase landfill diversion. Later, Luo et al. (2020) reported the use of SWOLF in combination with Reactive Nitrogen (Nr) flow assessment applied to a case study in China, highlighting the economic and environmental trade-offs of recycling SW.

Another SWOLF implementation was proposed by Jaunich et al. (2021) for policy analysis, aiming to incorporate more flexibility when selecting SWM strategies. These authors included feedback from SWM personnel to define and analyze revised strategies for an iterative optimization-based solution approach. However, their work was limited to the use of costs and GHG emissions as objectives.

3. Case study description

In this manuscript, the case study evaluates two social costs, total costs, and global warming potential (GWP) of the SWM system of the city of Columbia, Missouri, USA. An optimization-based approach is presented to minimize the impacts of these criteria and analyze their trade-offs. GWP is calculated according to CML 2001 over a 100-year time horizon (Hischier et al., 2010). The functional unit is the total mass of municipal solid waste (MSW) collected curbside in Columbia. The technologies that are currently operational in Columbia are landfill (LF), material recovery facility (MRF), and composting. SwolfPy considers that recyclables and yard wastes are collected separately for treatment in MRF and composting, respectively. The MRF is a sorting process in SWOLF and not a standalone treatment process, thus the selection of this process is followed by further treatment in a Reprocessing facility. All other wastes present in MSW (i.e., not yard waste or recyclables), referred to as residual waste, are collected separately and disposed of in the landfill.

The city of Columbia has a population of 126,254 with 2.31 persons per household according to the 2020 Census. The municipal solid waste composition generated from the residential sector is taken from a statewide study conducted in 2016–2017 by Missouri Department of Natural

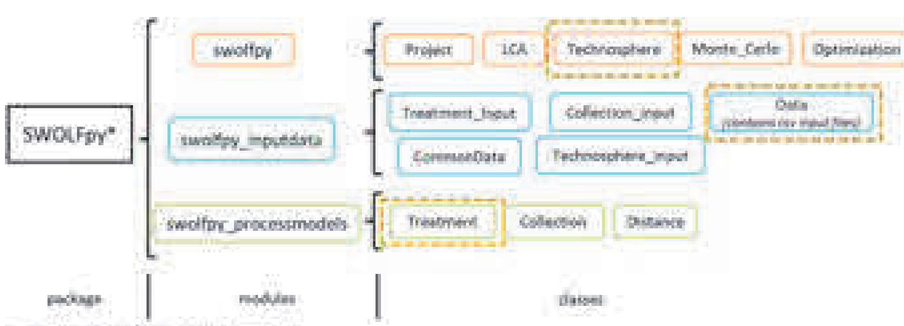

Fig. 1. An extract of SwolfPy classes, highlighting the classes that are modified in the extension proposed. Based on Sardarmehni et al. (2022).

Resources & MSW Consultants (2018) and modeled Columbia as a small metro. The residential waste generation rate used was 5.59 kg/person-day as calculated based on Equation (1) (Sardarmehni et al., 2022). A complete list of modelling parameters can be found in Appendix A.

$$\text{waste generation rate} = \frac{\text{Total waste}\,[\text{kg/year}]}{\text{Residents per house}\left[\frac{\text{person}}{\text{house}}\right]*\text{Number of houses}\,[\text{houses}]*\frac{365\ \text{days}}{1\ \text{year}}} \tag{1}$$

Social metrics exist within a wide spectrum, they could refer to satisfaction, public participation, employment potential, population affected, or visual pollution (among others), depending upon the specific stakeholders and the local context (Tokede and Traverso, 2020). Decisions made by stakeholders can directly influence the social impact derived from WM activities. We worked with stakeholders in Columbia, Missouri, USA to identify their social concerns and then developed quantitative indicators to address those concerns. Operational decision-making rests with the City of Columbia Solid Waste Utility, accordingly, we interviewed the five lead WM professionals from Columbia. We gathered background information about the site's operation, goals, and vision to understand their concerns and needs. Findings from the interview data analysis performed by White et al. (2023), show that the two topics of most concern to management are (1) general employee turnover and (2) avoiding injury risks associated with manually handling waste and while operating trucks.

4. Methodology

This section elaborates on the analytical process followed in this paper. The extension of SwolfPy framework is explained in Section 4.1 and the quantification of social metrics is presented in Section 4.2.

4.1. Extending SwolfPy

The original SWOLF framework includes cost and environmental criteria. These criteria are modeled using Life Cyle Impact Assessment (LCIA) methods. Each treatment process ("process model" in SWOLF nomenclature) is modeled independently using materials properties of waste and engineering equations to represent treatments. Model outputs are estimated per Mg for each incoming waste material (i.e., waste fraction, categorized into groups such as organics, paper, plastics, etc., Appendix B). The resulting materials and energy flows (e.g., diesel consumed, carbon dioxide emitted) of each process model is related to life cycle data in Ecoinvent v3.5 for these materials to calculate and aggregate an overall environmental LCA score. The LCA score is an aggregated measure that considers all treatment processes in the SWM system. SWOLF allows the user to choose environmental indicators from existing LCIA methods datasets such as TRACI, CML, IPCC, etc. When the single objective optimization occurs, it optimizes the LCA score for either costs or a selected environmental criterion, here the impact category climate change in units of global warming potential. Fig. 2 provides an illustration of this LCA computation process.

The social indicator follows the same structure as the estimation of materials and energy when estimating the social cost for each process within the SWM system. That is, each process model is modified such that the social indicator is computed individually in each process and then aggregated to present a final social score, all using a common social unit for social indicators. It is not a full life cycle perspective, because only the social costs incurred within Columbia, MO waste management are accounted for. Appendix C provides a more-detailed explanation of the specific changes made to the SWOLF code and input files. Thus, the LCA score as adopted by SWOLF to measure social aspects differs from S-LCA in the definition of the social indicators. We focused the creation of indicators based on stakeholders inputs; moreover, as our objective is to aid decision making via optimization, we provide a procedure to obtain quantitative indicators as explained in Section 4.2.

Equation (2) presents a mathematical representation of the local social indicator score, which is defined as the summation of the individual contribution per waste material per treatment process to the social impact metric.

$$\text{LCA social score} = \sum_i \sum_j f_{ij} \sum_k soc_{ijk} \tag{2}$$

where,

f_{ij} = **total flow of material** i from treatment process j.

soc_{ijk} = **social impact** k of one unit of flow of material i from treatment process j.

4.2. Creating quantitative social metrics

Social metrics have unique features that complicate their quantification process. Social metrics can depend on the local setting, the stakeholders' interests, and the decisions under consideration, among other things. We followed the process layout presented in Fig. 3 to understand the needs and quantify two social metrics of interest.

The City of Columbia interviewees acknowledged that the WM job is physically demanding and while the city employee benefits were strong, the pay level was reported as a reason for turnover. Consequently, SWM workers often leave after a short tenure in their position, which contributes to understaffing. The pay level was viewed by the WM professionals as outside of their control, because, like other municipal employees, the pay structure and benefits are determined through city governance, and was thus excluded from our metric. In summary, by combining input from WM stakeholders and the literature, we focused our efforts on developing metrics to address worker safety and turnover.

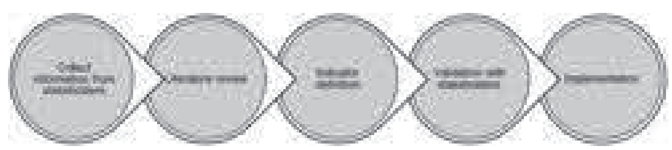

Fig. 3. Social metrics quantification process.

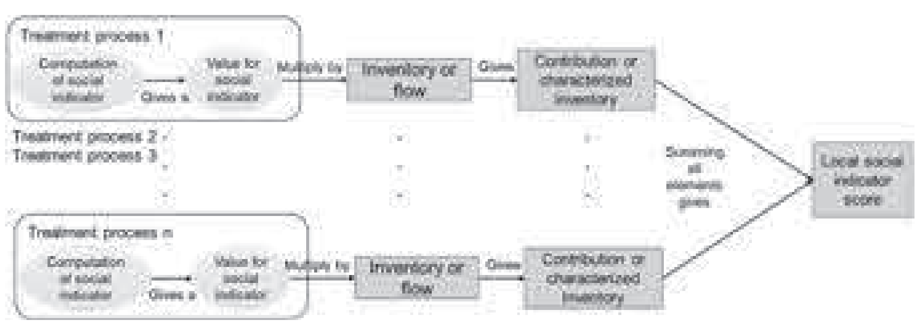

Fig. 2. Illustration of computations in SWOLF for local social metrics.

Based on stakeholders' concerns, we reviewed literature on ergonomics, pay-level, and turnover in general and in WM contexts. Unsurprisingly, we found pay level has a positive relationship with employer attractiveness and retention (Rynes et al., 2004; Waples and Brachle, 2020). Moreover, turnover is motivated by jobs with increased physical demands (Ferguson et al., 2014) and that a climate of workplace safety has a relationship with turnover intention and job satisfaction (McCaughey et al. (2013). Accordingly, better safety climate perceptions and training opportunities can significantly increase job satisfaction and employee retention (Huang et al., 2016; Balogun et al., 2020; Smith, 2018). It is imperative to explain to workers the correct working procedures and manual material handling (MMH) practices to avoid awkward postures, incorrect movements, and person-dependent working approaches that can lead to increased risk levels (Battini et al., 2018; Botti et al., 2020).

4.2.1. Worker's physical exposure

Estimates for the social metric termed, Worker's Physical Exposure (WPE), were calculated for each waste typology, i, and treatment process, j, following the conceptual framework shown in Fig. 4. In summary, risk associated with each combination of i and j were estimated in $/ton based on workload, ergonomic risk and the cost associated with worker injury.

MMH results in the largest fraction of work-related musculoskeletal disorders (WMSDs) for workers in collection, transport, and treatment of non-dangerous waste (Botti et al., 2020; Bunn et al., 2011; Mol et al., 2017). The ergonomics analysis in previous studies presented risk assessments of SWM activities using methodologies as NIOSH Variable Lifting Index (VLI) for evaluating variable lifting tasks and Rapid Entire Body Assessment (REBA) in combination with Rapid Upper Limb Assessment (RULA) for postural analysis. In addition, driving activities (e.g., collection trucks, compactors, or crawlers) pose another risk. There is a relationship between whole-body vibration (WBV) and musculoskeletal disorders (MSD) mainly due to the absorption and dissipation of forces as a result of long sitting times in machinery (Moraes et al., 2016).

Data from ergonomic studies were taken from the literature and related to each treatment process and material in SWOLF (Appendices D and E). We estimated the workload of workers on a year using frequency of activities, time exposure, and weight exposure (Fig. 4). The activities considered during waste management are lifting, carrying, emptying, placing, and sitting. The time exposure to these activities was taken from Rossi et al. (2022), and the weight load exposure for these same activities was taken from Ferguson et al. (2014). The percentage of time dedicated to MMH for collection is assumed to be 47% (Botti et al., 2020), while for treatment processes manual activities are assumed to constitute 83% (Degli Esposti et al., 2023). Frequencies of activities based on waste typology are assumed in activities per minute according to data presented by Rossi et al. (2022). Waste typology classification (Botti et al., 2020; Rossi et al., 2022) is translated into six categories that correspond to high level categories of waste fractions in SWOLF. These are: organic, paper, glass, metals, plastics, and other.

Risk assessment is considered by waste typology and activities in a scale ranging from low to very high according to NIOSH VLI and RULA index as shown in Table 3. Lifting, carrying, and emptying risk is taken from Rossi et al. (2022) and Botti et al. (2020). The risk associated with the placing activity is assumed to be the same as carrying activity. Carrying and placing activities shared similar physical efforts as the weight load exposure involved in each one is equivalent in the ergonomic study by Ferguson et al. (2014); hence, both activities have been assigned a common risk level. The emptying activity represents the highest risk as in this situation workers need to overturn or toss waste contents into the truck container. Organic waste is considered riskier as workers tend to keep the load far from the body to avoid splashes from wet waste. A similar phenomenon is presumed for yard trimmings and leaves, as workers need additional shaking to empty containers and other safety issues due to contact with thorns and sticks.

The risk assessment for driving activities utilized previously published measures of whole-body vibration (WBV) on a driver (Kim et al., 2016; Maeda and Morioka, 1998; Smets et al., 2010) based on the International Standard Organization (ISO) 2631-1 WBV standards. Reference values used to represent driving impact on WPE due to processes (e.g., LF, WTE, collection) in SWOLF ranged from 0.44 to 0.80 m/s^2 (Smets et al., 2010). These values are within the health guidance caution zone, which is mostly above action limit (0.5 m/s^2) but overall, below daily exposure limit (1.15 m/s^2). Additional information is presented in Table B-7, C-5, and C-6 in the Appendix.

Finally, we estimated average costs values of $1,590, $26,120, $62,660 for each level of disability using (i.e. $/incident) information from a report of costs by type of disability considering data from 2015 to 2018 according to the Missouri Department of Labor and Industrial

Table 3
Risk associated based on material and activity performed.

Material	Lifting	Carrying	Emptying	Placing
Organics	Moderate	Moderate	Very High	Moderate
Paper	High	Moderate	High	Moderate
Plastics	Moderate	Moderate	High	Moderate
Metal	Moderate	Moderate	High	Moderate
Glass	High	Moderate	High	Moderate
Other	High	Moderate	High	Moderate

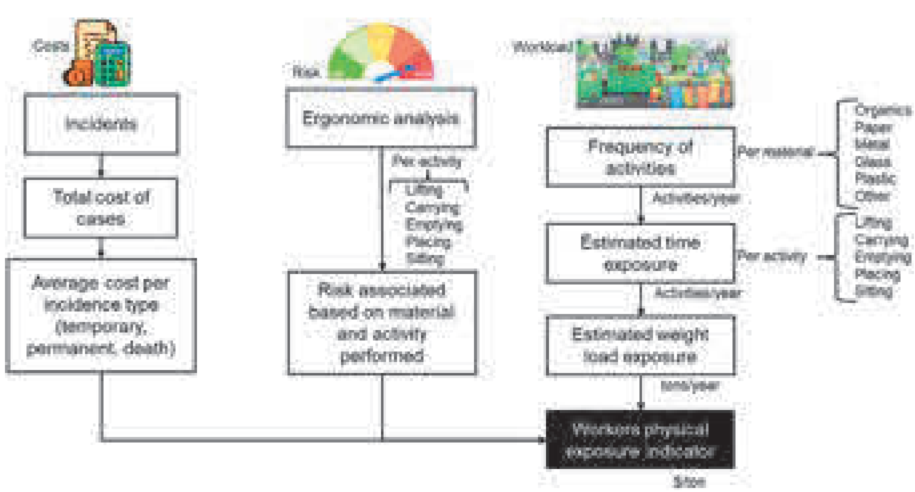

Fig. 4. Conceptual Framework to estimate Worker's Physical Exposure Indicator.

Relations. Occupational incidents are grouped into three types depending on the severity of the disability caused; these types are temporary, permanent, and death (Missouri Division of Workers' Compensation, 2018).

4.2.1.1. Algorithm. The algorithm presented in Table 4 was applied to estimate the worker's physical exposure indicator. Estimates obtained by following this algorithm are provided in Appendix F.

4.2.2. Turnover

Estimates for the turnover social metric were developed for each waste typology i, and treatment process, j, following the conceptual framework presented in Fig. 5. In summary, impact associated with each combination of i and j were estimated in $/ton based on workload, loss productivity, quit rate, and the cost associated with hiring and replacing a worker that voluntarily quits.

Turnover can be voluntary (i.e., worker-initiated, such as

Table 4
Algorithm for Worker's physical exposure indicator Estimation.

Algorithm 1: Workers' Physical Exposure Indicator Estimation

input: f_{ij}: frequency of MMH activities per waste typology i and treatment process j (activities/min)
s_min: work-shift length (min/day)
s_days: work-shift length (days/year)
t_{kj}: time exposure per manual activity k and treatment process j (s)
p_j: percentage of time dedicated to MMH activities per treatment process j
w_{kj}: weight load exposure per manual activity k and treatment process j (N)
r_{ijk}: risk associated per waste typology i treatment process j and manual activity k
c_m: average costs per incident type m ($)
ρ_j: estimated tons per day per truck/machine per treatment process j
α_j: risk associated to sitting activity per treatment process j
output: WPE_{ij}: workers' physical exposure indicator per waste typology i and treatment process j

1 **For** each treatment process j
2   **If** treatment process j has only sitting activity **then**
3     $\delta_{ij} = 0$, Go to stetp 22
4   **End if**
5   **For** each waste typology i
6   Transform f_{ij} to activities/year, $new\_f_{ij} = f_{ij} * s\_min * s\_days$
7   **For** each manual activity k
8   Compute fraction of time exposure, $\theta_k = (t_{kj} / \sum_k t_{kj}) * p_j$
9   **For** each waste typology i and manual activity k
10   Compute fraction of workload, $\omega_{ijk} = new\_f_{ij} * \theta_k$
11   Transform workload to tons, $\tau_{ijk} = \omega_{ijk} * (1.01972 \times 10^{-4} * w_{kj})$
12   **If** $r_{ijk} = moderate$ **then**
13       $\varphi_{ijk} = c_{temporary} / \tau_{ijk}$
14   **else if** $r_{ijk} = high$ **then**
15       $\varphi_{ijk} = c_{permanent} / \tau_{ijk}$
16   **else**
17       $\varphi_{ijk} = c_{death} / \tau_{ijk}$
18   **End if**
19   **For** each waste typology i
20     $\delta_{ij} = \sum_k \varphi_{ijk}$
21   **If** treatment process j has sitting activity **do**
22   **If** $\alpha_j = moderate$ **then**
23       $\beta_j = c_{temporary} / \rho_j$
24   **else if** $\alpha_j = high$ **then**
25       $\beta_j = c_{permanent} / \rho_j$
26   **else**
27       $\beta_j = c_{death} / \rho_j$
28   **end if**
29     $WPE_{ij} = \delta_{ij} + \beta_j$
30   **else**
31     $WPE_{ij} = \delta_{ij}$

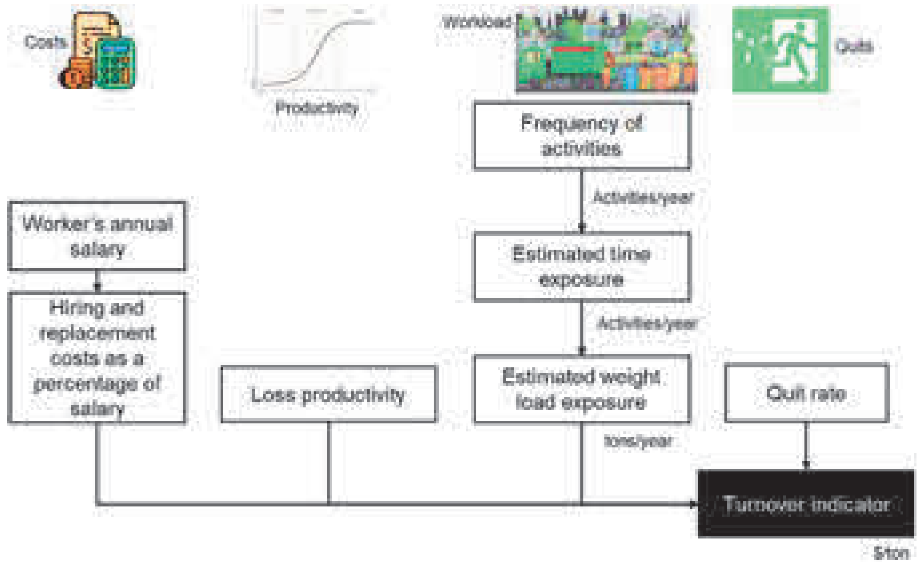

Fig. 5. Conceptual Framework to estimate Turnover.

resignations) and involuntary (i.e., employer-initiated, such as termination for poor performance) (O'Connell and Kung, 2007) In this research, we are interested in voluntary turnover, as waste management professionals interviewed shared that workers quit with high frequency. Ongori (2007) argued that voluntary resignations represent a departure of human capital investment, and the replacement process involves several costs to the organization. Cost components associated with turnover according to O'Connell & Kung (2007) include 1) staffing such

Table 5
Algorithm for turnover indicator Estimation.

Algorithm 2: Turnover Indicator Estimation

input: $\boldsymbol{\delta_{ij}}$: workload in tons per year per waste typology $\boldsymbol{i}$ treatment process $\boldsymbol{j}$
$\boldsymbol{c_j}$: average costs of hiring and training a new worker per treatment process $\boldsymbol{j}$ ($)
$\boldsymbol{\rho_j}$: estimated tons per year per truck/machine per treatment process $\boldsymbol{j}$
$\boldsymbol{\alpha}$: quit rate
output: $\boldsymbol{T_{ij}}$: turnover indicator per waste typology $\boldsymbol{i}$ and treatment process $\boldsymbol{j}$

1 **For** each treatment process $\boldsymbol{j}$
2 **If** treatment process $\boldsymbol{j}$ has only sitting activity **then**
3 $\boldsymbol{\Gamma_{ij} = 0}$, Go to stetp 13
4 **End if**
5 **For each waste typology $\boldsymbol{i}$**
6 Compute loss productivity first month, $\boldsymbol{\mu\_1_{ij} = (\delta_{ij}/12) * 0.25}$
7 Compute loss productivity second month, $\boldsymbol{\mu\_2_{ij} = (\delta_{ij}/12) * 0.50}$
8 Compute loss productivity third month, $\boldsymbol{\mu\_3_{ij} = (\delta_{ij}/12) * 0.75}$
9 Normal productivity from month 4 to 12, $\boldsymbol{\mu\_4_{ij} = (\delta_{ij}) * 0.75}$
10 $\boldsymbol{\xi_j = c_j/\mu\_1_{ij} + c_j/\mu\_2_{ij} + c_j/\mu\_3_{ij} + c_j/\mu\_4_{ij}}$
11 $\boldsymbol{\Gamma_{ij} = (\xi_j * \alpha)}$
12 **If** treatment process $\boldsymbol{j}$ has sitting activity **do**
13 Compute loss productivity first month, $\boldsymbol{\vartheta\_1_j = (\rho_j/12) * 0.25}$
14 Compute loss productivity second month, $\boldsymbol{\vartheta\_2_j = (\rho_j/12) * 0.50}$
15 Compute loss productivity third month, $\boldsymbol{\vartheta\_3_j = (\rho_j/12) * 0.75}$
16 Normal productivity from month 4 to 12, $\boldsymbol{\vartheta\_4_j = (\rho_j) * 0.75}$
17 $\boldsymbol{\lambda_j = c_j/\vartheta\_1_j + c_j/\vartheta\_2_j + c_j/\vartheta\_3_j + c_j/\vartheta\_4_j}$
18 $\boldsymbol{T_{ij} = \Gamma_{ij} + (\lambda_j * \alpha)}$
19 **Else**
20 $\boldsymbol{T_{ij} = \Gamma_{ij}}$
21 **End if**

as recruiting and hiring, 2) vacancy that entails loss productivity or loss business, and 3) training which refers to orientation and development. The quit rate reflects the worker's willingness to leave a job. This value considers only employees who left voluntarily, excluding retirements or transfers to other locations.

Data from previous studies and reports were taken from the literature and related to each treatment process and material in SWOLF. Hiring and training a replacement worker for a lost employee costs approximately 50% of the worker's annual salary (Ongori, 2007). According to the Occupational Employment and Wage Statistics Data the national average annual salary for Waste Collection (NAICS 562100) was $51, 210 and for Waste treatment and disposal (NAICS 56200) was $59,380 in 2022 (U.S. Bureau of Labor Statistics, n.d.).

There is a learning curve for a new employee (Ongori, 2007) that can be translated into the economic value associated with the loss of labor productivity and efficiency relative to the output over the first three months (Duda and Žůrková (2013). In this analysis, it was assumed that a new employee works at 25% of capacity in the first month, during the second month at 50%, in third month at 75%, and beyond 3 months at a full 100%. The average annual quit rate of the state of Missouri was 28.8% based on data from 2013 to 2022 across all industries (U.S. Bureau of Labor Statistics, 2023). Finally, the workload assumption for workers and drivers (tons per year) is assumed to be the same as in the previous metric Worker's Physical Exposure.

4.2.2.1. Algorithm. The algorithm presented in Table 5 was used to estimate the Turnover Indicator. Estimated values obtained by following this algorithm are provided in Appendix G.

5. Results and discussion

First, in Section 5.1 we present the values determined for the local social metrics described in Section 4.2.1 and 4.2.2. Then, Section 5.2 elaborates on the case study scenarios used to illustrate the model and its potential implications; in Section 5.3, we conduct sensitivity analysis, considering changes to the local social metric input values.

5.1. Estimates for social metrics

Implementing algorithms 1 and 2, we obtained estimates for the social metrics as shown in Tables 6 and 7. More details about these estimates can be found in Appendix F and G. Among technologies, Material Recovery Facility (MRF), Anaerobic Digestion (AD), and Composting social values were greater than Landfill (LF) and Waste to Energy (WTE), with WTE having the lowest social cost value. This difference in values is because MRF, AD, and Composting technologies require more manual components than LF and WTE. Because waste materials are often handled separately, or even separated by workers in the MRF, it is possible to create metrics by waste typology for MRF, AD, and Composting; while for LF and WTE a mix of waste is handled primarily by machines, with the exception of tossing bags into a truck during collection. Loss of productivity is negligible for machine driven technologies (Table 7) which contributes to smaller Turnover impact than with manual technologies (Table 6). Overall, smaller values are better for these social metrics. For instance, our estimates for WPE indicate that handling materials such as organics, paper, and plastics are safer than manipulating glass and metal.

Table 6
Social metrics estimates for MRF, AD, and Composting treatment options.

	Worker's Physical Exposure [$/ton]	Turnover [$/ton]
Organics	36.90	98.34
Paper	44.07	43.71
Plastics	29.52	78.67
Metal	147.61	393.36
Glass	99.16	98.34
Other	29.38	29.14

Table 7
Social metrics estimates for Landfill (LF) and Waste to Entergy (WTE).

	Worker's Physical Exposure [$/ton]	Turnover [$/ton]
LF	53.53	0.56
WTE	4.07	0.70

5.2. Case study scenarios

Scenarios were evaluated in SwolfPy to find the mix of mass flows of waste to treatment technologies that minimizes the local social metric, total costs, and GHG emissions (see Table 8).

Scenarios 1–3 explored the selection of technologies when optimizing for one social indicator or both simultaneously. Scenario 4 includes the addition of two technologies and both social indicators. The addition of these new technologies expands the decision space. Comparison of the results of this scenario analysis offers insights on the trade-offs among social metric, costs, and GHG emissions.

Results from scenarios 1, 2, and 3 were similar in terms of technology mix selection, diversion, total costs, and GHG emissions. Consequently, results for scenarios 1 and 2 were not shown; instead we present results for scenario 3 in Fig. 6. Given that materials sorting by workers increases material manual handling, diversion of materials to the MRF for subsequent recycling is not selected when optimizing for the social metric, Fig. 6. However, due to the assumptions in SwolfPy that grant greenhouse gas avoidance credits and economic value to recycled materials, these options are selected when optimizing to minimize cost or GHGs, Fig. 6.

When comparing the two indicators of the social metric, Scenario 3, results indicate that turnover contributed less cost than the WPE under each objective, due to most of the waste being landfilled and LF turnover values were the smallest (i.e. 0.56 $/ton). The most expensive total cost occurs when minimizing the social metric, while the most expensive social metric occurs either when minimizing costs or GHG. Again, this result reflects the additional WPE, and corresponding increased risk of Turnover associated with materials handling (see Table 9).

When allowing for new treatment technologies in Scenario 4, the selection of treatment technologies varies given optimization criteria (Fig. 7 and Table 10). WTE is selected for most of the waste when social or GHG metrics are the optimization target. WTE is selected based on social indicator due to relatively low handling of materials. Likewise, recycling, which is mediated by the MRF is the reason that MRF is not selected when optimizing the social indicator, Table F-5 in Appendix F. Although AD was available as a treatment technology, this was not chosen by any of the optimization criteria due to its being a more operationally expensive technology with significant manual material handling. When costs were of interest, LF and MRF were selected, whereas for the GHG objective LF, MRF and WTE were preferred.

The highest diversion of MSW from the landfill is reached by minimizing GHGs through selecting WTE, LF, and MRF at the expense of

Table 8
Scenario descriptions for technology options and social indicators in optimization.

Scenario	Technology	Worker's Physical Exposure	Turnover
1	Current mix	✓	
2	Current mix		✓
3	Current mix	✓	✓
4	Current mix + AD and WTE	✓	✓

Note. Current mix includes landfill, compost, and material recovery facility. AD = anaerobic digestion. WTE = 'waste-to-energy,' here incineration with electricity generation.

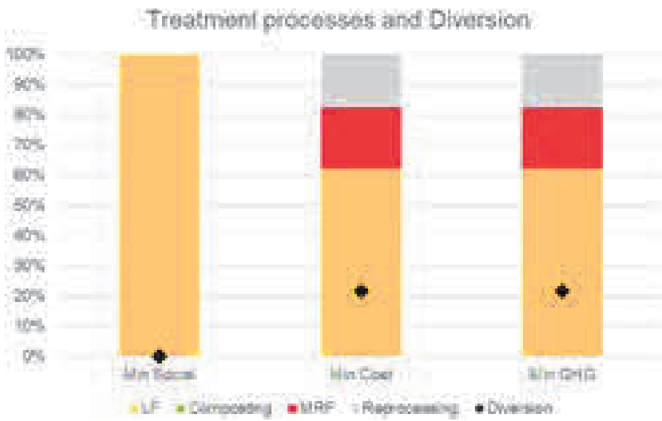

Fig. 6. Results from Scenario 3. Technology mix and diversion.

Table 9
Optimization results Scenario 3.

	GWP [kg CO_2e/Mg]	Total Cost [$/Mg]	Worker's Physical Exposure [$/Mg]	Turnover [$/Mg]	Social metrics [$/Mg]
Min Social	−52.71	52.47	**164.96**	**42.27**	**207.23**
Min Cost	**−316.17**	**25.75**	217.78	104.62	322.4
Min GHG	**−316.17**	**25.75**	217.78	104.62	322.4

Bold values indicate the minimum cost achieved for each cost category.

higher social metric values. Diversion scenarios were not explored further; however, this finding reveals an alternative option for sending less waste to the landfill which contributes to one of Columbia's policy goals (City of Columbia, 2019).

5.3. Sensitivity analysis

Given the uncertainties associated with our social metric estimates, we conducted additional analyses to determine how changes to the assumed social metric values would influence the optimal technology mixes identified by our optimization model. Recall from Tables 6 and 7 that the Worker's Physical Exposure costs for WTE were an order of magnitude smaller than the costs for many waste materials under MRF, AD and Composting. This likely influences the heavy utilization of WTE under the solution minimizing the social cost objective (Fig. 7).

Therefore, in our sensitivity analysis we assumed that the WTE risk levels would be increased from the range low – moderate to high risk (increasing the Worker's Physical Exposure cost for WTE from 4.07 to 66.91 dollars per ton). In total, eight new scenarios were developed for potential reductions to both Worker's Physical Exposure and Turnover costs for MRF, AD, and Composting, Table 11. For this experiment, our "high" level, denoted in Table 11 by an " = ", represents no change to original values (Table 6), while the "low" level, denoted by an "-" assumes a 90% decrease (improvement) to these social cost values for each waste material. Such cost reductions for MRF, AD and Composting could be achieved by implementing the use of devices or tools to assist workers with MMH activities (e.g. switching to rolling carts for waste collection purposes) along with reinforcement trainings in ergonomics, or automated sorting technologies.

The optimal technology mixes identified by our models differed depending on the scenario, as illustrated in Table 11. Note that LF was utilized in every scenario, this was expected as waste products from most processes end up in the LF (e.g. bottom ash).

This sensitivity analysis found that Composting was selected in all scenarios (B, C, F, H) when its social costs were reduced and in no scenarios when its social costs were unchanged. Similarly, AD was selected in scenarios where its social costs were reduced and the social costs of Composting were not reduced (A, D). MRF was not selected in any instance where social costs were minimized. WTE was utilized in four of these scenarios (A, B, F, H), generally in combination with Composting. Observe that the GWP metric was significantly worse for these eight scenarios, in which the social metric objective was minimized, relative to the GWP values obtained under the baseline social costs in Table 10. This occurs due to the selection of LF to treat most of the waste in these sensitivity analysis scenarios, avoiding technologies with increased material handling.

These sensitivity analyses suggest that there is no dominant solution for technology mix in this city's example, thus, such a determination would depend on the stakeholders' relative weighting of the multiple objectives. Focusing on social metrics, we observe that under our baseline estimates of social costs (Fig. 7), LF and WTE are the preferred technologies. Scenarios in which WTE Worker's Physical Exposure costs are increased and Composting social costs are decreased show a preference for the use of LF, WTE and Composting. AD replaces Composting in the solution when its social costs, but not the social costs of Composting, are decreased. MRF is never selected when minimizing social costs. However, when the objective is to minimize either Total Costs or GHG (Fig. 7), neither AD nor Composting were ever selected, with the solutions preferring LF, MRF and (in the case of the minimum GHG objective) WTE. Although we consider it good to have more variety in the technology mix, this could potentially become impractical if a small percentage of waste is treated in one technology. Further analysis could explore utilization constraints to require a minimum level of use such that throughput is maintained at a desired level.

These results could be utilized for evaluation of policy alternatives. For instance, feed-in tariff policies can be analyzed to support waste management procedures, especially when the focus is on mitigating GHG emissions (Chen and Liu, 2021); however, some authors have discussed that government subsidy in technology could provide better benefits (Li et al., 2023). In the case of Columbia, MO, the city has a climate & adaption action plan with very aggressive goals in place (City of Columbia, 2019). These goals target GHG emissions, landfill diversion, and recycling rates. Although these specific targets were not addressed in this analysis, we observed some benefits in terms of landfill diversion. If the city desired to add social sustainability considerations to

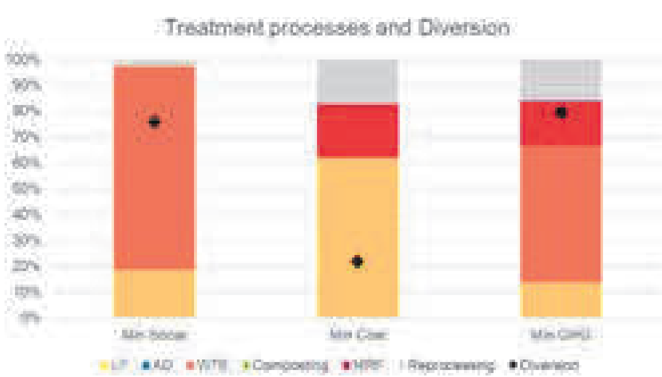

Fig. 7. Results from Scenario 4. Technology mix and diversion.

Table 10
Optimization results Scenario 4.

	GWP [kg CO2e/Mg]	Total Cost [$/Mg]	Social metric [$/Mg]
Min Social	−302.74	69.59	**170.81**
Min Cost	−317.47	**25.78**	322.3
Min GHG	**−445.52**	43.6	294.82

Bold values indicate the minimum cost achieved for each cost category.

Table 11
Technology mix results from sensitivity Analysis.

						Technology Mix					Optimization Results
Scenarios	MRF	AD	Comp	Description	Optimization Criteria	LF	MRF	Comp	AD	WTE	Social Metric ($/Mg)
A	=	-	=	Improve only AD	Min Social						**68.47**
					Min Costs						101.61
					Min GHG						123.11
B	=	-	-	Improve AD & Comp	Min Social						**68.13**
					Min Costs						101.55
					Min GHG						123.11
C	=	=	-	Improve only Comp	Min Social						**68.12**
					Min Costs						101.62
					Min GHG						123.11
D	-	-	=	Improve MRF & AD	Min Social						**68.46**
					Min Costs						70.38
					Min GHG						91.87
E	-	=	=	Improve only MRF	Min Social						**207.23**
					Min Costs						70.38
					Min GHG						91.87
F	-	=	-	Improve MRF & Comp	Min Social						**68.13**
					Min Costs						70.35
					Min GHG						91.87
G	=	=	=	No improvements	Min Social						**207.23**
					Min Costs						322.42
					Min GHG						343.96
H	-	-	-	Improve MRF, AD & Comp	Min Social						**68.13**
					Min Costs						70.31
					Min GHG						97.87

Notes: Bold values indicate the minimum social cost achieved. Colored shading indicates some portion of waste was treated with the corresponding technology; the diagonal stripe hatching indicates less than 1000 tons of waste was treated in that technology; white/blank cells indicate the technology was not selected.

these target values, an approach similar to that of this analysis could be used to estimate these social costs in terms commensurate with the existing environmental goals.

6. Conclusions

SWM strategies need to be tailored to the specific needs of the system in place, accordingly, the examination of multiple criteria is required. Traditionally, capital, and operational costs along with environmental impacts have been addressed in the literature. This study ventures to introduce social metrics into consideration for decision making in waste management.

We propose a process for the quantification of social metrics involving stakeholders into the development. It is important to initiate this task with input from stakeholders as social metrics are system-specific—contingent on context—and not every potential social consideration found in the literature is necessarily applicable to every system (Fritz et al., 2024). Nor are those metrics equally important to managers and decision makers. Involving stakeholders in this process facilitates the understanding of the context and the selection of meaningful metrics (Hall et al., 2024). Further, it can motivate the adoption of results for decision-making.

Based on the information received from stakeholders, we focused our social metrics on the solid waste workers. The metrics developed were Worker's Physical Exposure and Turnover. These social metrics can help WM authorities to measure and control Occupational Safety and Health Administration (OSHA) standards within their organizations. OSHA protects workers and prevents work-related injuries, illness, and deaths. Although not every state and local government worker in United States is within federal OSHA jurisdiction, interventions to address these issues can present benefits such as less workers' compensation costs, reduced employee turnover, and increase in work efficiency and productivity. In addition, accounting for such considerations can help employers avoid potential employees' complaints or inspections of the workplace by a regulatory entity.

We provided estimates for these metrics based on the literature from ergonomics and employee turnover that best fit our WM setting. These metrics can help WM authorities to be better prepared to comply with law and regulations such as OSHA. Detailed algorithms quantifying each metric were presented. Although other applications would require fine-tuning to the specific considerations of that system and its stakeholders, we anticipate that the structure of these algorithms could serve as baselines for other social metrics.

These social metrics were integrated into the LCA-based optimization framework SWOLF (Levis et al., 2013; Sardarmehni et al., 2022). Results from a case study based on the city of Columbia, MO illustrate that technology mix selection is dependent upon the criterion of interest. For instance, WTE was preferred when the desire was to minimize GHG, while Composting and AD were preferred under an objective minimizing PWE and Turnover. We tested improvements that targeted better worker conditions boosting safety and retention; under these circumstances' manual treatment technologies had a more prominent role. Moreover, we were able to identify the trade-offs that accompany these conflicting criteria in waste management, as it exists in our case study community.

- The best social score, and the highest total cost, is obtained at the expense of less landfill diversion.
- The best environmental score is obtained at the expense of the highest social costs.
- The best cost score is obtained with intermediate social costs and landfill diversion.

Future research studies might focus on other social metrics that point to customers or waste management authorities instead of workers, or other parts of the overall supply chain. In addition, there is a wide range of space for policy analysis. Future research could add constraints to the modeled scenarios to analyze policy goals such as lawmakers' desired changes to diversion or recycling rate targets. The implications of each policy scenario could be compared for impacts on not just on physical operations but the social operations as defined and prioritized by the acting organizations. Finally, a continuation to this research could move from the single objective models utilized in this paper to a multi-objective optimization to further explore the tradeoffs between the three criteria discussed in this study.

CRediT authorship contribution statement

Jenny Gutierrez-Lopez: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ronald G. McGarvey:** Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **James S. Noble:** Writing – review & editing, Supervision, Resources, Investigation. **Damon M. Hall:** Writing – review & editing, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Christine Costello:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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Declaration of competing interest

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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.2024.144111.

Data availability

Data will be made available on request.

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