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Additional Information

Prioritizing action plans to save resources and better achieve municipal solid waste

management KPIs: an urban case study

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Abstract:

 The management of municipal solid waste (MSW) in cities is one of the most complex tasks facing local administrations. For this reason, waste management performance measurement structures are increasingly implemented at local and national levels. These performance structures usually contain strategic objectives and associated action plans, as well as key performance indicators (KPIs) for 17 organizations investing their resources in action plans. This study presents the results of applying a methodology to find a quantitative-based prioritization of MSW action plans for the City Council of Castelló de la Plana in Spain. In doing so, cause-effect relationships between the KPIs have been identified by applying the principal component analysis technique, and from these relationships it was possible to identify those action plans which should be addressed first to manage public services more efficiently. This study can be useful as a tool for local administrations when addressing the actions included in their local waste plans as it can lead to financial savings.

- **Keywords**: MSW; action plans; KPIs; principal component analysis
-

1. Introduction

 The increasing amount of food waste generated as a direct consequence of excessive production, mismanagement, and wasteful behavior is a challenge when promoting resource efficiency (Facchini et al., 2018). One of the objectives of European policy on waste is to move towards a circular economy (Ferronato et al., 2019). Since the publication of the community waste management strategy in 1989, the implementation of principles for material circularity and waste management has been intensifying (Singh & Ordoñez, 2016). Furthermore, governments around the world have long been committed to developing plans for the sustainable use of resources by strategies that affect waste management (Wilson et al., 2001).

 In Spain, these directives have had a direct impact on municipalities, and they have been required to develop local waste management plans and programs (Spain, 2022). These plans establish the conditions and means to manage the waste produced by the activities of a city – with priority on source reduction. These plans and programs are well monitored and managed when an adequate key performance indicator (KPI) grid for assessing, controlling, and improving effectiveness is defined (de Pascale et al., 2021). Additionally, the KPIs are an element of a performance measurement structure that usually includes both objectives and action plans.

 When looking at performance measurement (PM) theory and, more specifically, at the best-known and applied PM framework, the Balanced Scorecard (Kaplan & Norton, 1992), organizations interpret their strategic definition (mission, vision, and values) to firstly define their strategic objectives (what to reach) and then define action plans (how the strategic objective will be reached) and KPIs (to indicate whether the strategic objective is being reached). However, public administrations do not usually follow this performance measurement structure. These organizations manage their performance only using KPIs, and when they define the whole measurement structure, they do not apply the tools available to improve effectiveness.

 There are many academic works focused on assessing sustainability KPIs (Hristov & Chirico, 2019; Kylili et al., 2016; Pinna et al., 2018; Valencia et al., 2022) including waste management KPIs (Ferreira et al., 2020). However, these works usually only address the tasks of definition and historical data collection for KPIs, and do not carry out a sound analysis of the evolution of the values of the KPIs, nor apply appropriate mathematical techniques to identify additional information for making better decisions. These practices are therefore far from being the most efficient way to proceed. In most cases, the KPIs are usually related (Carlucci, 2010), which means that changes in the values of some KPIs produce changes in the values of other KPIs – and so change the performance of the system. Further, the identification of cause-and-effect relationships between the KPIs makes it possible to prioritize actions plans and improve the effectiveness of the whole performance system structure – as decision-makers can apply actions that enable reaching associated strategic objectives, as well as other resource-saving objectives.

 This work refers to a case study in the city of Castelló de la Plana (Spain), and its main contributions are the following: a) it identifies and classifies the principal KPIs for municipal solid waste (MSW) management at the local level in the three dimensions of sustainability; b) it identifies, by applying the historical data collected by the KPI statistical techniques, the main intra and extra dimensional cause-effect relationships between KPIs; c) it prioritizes the action plans, based on these cause- effect relationships, which help optimize municipal resources since it may not be necessary to activate every action plan to reach the KPI targets – and thereby improving the efficiency of local MSW management.

 The remainder of this paper is structured as follows: Section 2 provides a background of previous academic works on waste management and performance measurement. The research approach is presented in Section 3, and Section 4 shows and discusses the main results of applying such a methodology to the city of Castelló de la Plana (Spain). Finally, Section 5 provides the main conclusions, describes the limitations of the study, and suggests further research work.

2. Background

 Planning in the provision of public services is becoming increasingly frequent, and so the use of indicators to measure performance has also become widely used in the local sphere. Studies have been made on using KPIs in urban design (Mosca & Perini, 2022), transport (Grote et al., 2021), communications (Imoize et al., 2022), wastewater treatment (van Schaik et al., 2021), air quality (Malm et al., 2018) and MSW management (Ferreira et al., 2020).

 Focusing on the latter issue, during the last five years there have been more than 3,000 references 83 to KPIs dealing with MSW management. Some of these works focus on a specific perspective of the problem, such as the social (Ibáñez-Forés et al., 2019), the economic (Zhou et al., 2022), or the fractions that have been increasing most rapidly in recent years (Brouwer et al., 2019); while others evaluate the overall efficiency of the system (Amaral et al., 2022). There are also studies that summarize the literature about MSW KPIs and establish commonalities between different countries and years (Deus et al., 2019; Olay-Romero et al., 2020). Some go even further and use literature from other subjects for the development of communication campaigns (de Feo et al., 2019) or educational applications (Pappas et al., 2021).

 However, only a few studies (Nemmour et al., 2022) analyze the relationship between indicators for waste management. Although these KPIs are often related, it is important to understand these relationships for efficient decision-making processes (AlHumid et al., 2019; Loizia et al., 2021) as well as in the management of available resources (Stricker et al., 2017).

 Several studies can be found that apply statistical techniques to identify KPI cause-effect relationships in MSW management. For instance, (Hatik & Gatina, 2017) used principal component analysis (PCA) to identify similarities between local administrative areas for comparing waste composition; (Callas et al., 2012) defined an indicator of solid waste generation potential in the USA using principal component analysis and geographic information systems; (Liu et al., 2023) assessed soil pollution and identified potential sources of heavy metals with a combination of a spatial distribution and the principal component analysis model. Other studies about waste management use correlation analysis, (Barbudo et al., 2012) for example, assessed the correlation between sulphate content and leaching of sulphates in recycled aggregates from construction and demolition wastes; and (Birgen et al., 2021) developed a data analysis method based on correlations applied to waste-to-energy plants; and (Zhang et al., 2023) recently used correlational analysis to observe how digestion temperature affects the anaerobic digestion of food waste.

 Finally, although there are several studies about how to undertake action plans in local waste management plans or programs, most are limited to a descriptive analysis (Asibey et al., 2021) or, at best, they use multi-criteria techniques (Andrade Arteaga et al., 2020; Coban et al., 2018; Habibollahzade & Houshfar, 2020) that are limited to expert opinions (instead of real data collected by KPIs) and are therefore completely subjective.

 Some academic works from other disciplines have discussed identifying and quantifying KPI cause- effect relationships with statistical techniques to improve decision-making processes. For instance, (Rodríguez-Rodríguez et al., 2020a) applied PCA and partial least squares models to draw a KPI cause-effect map for supply chains to improve operational efficiency; (Sanchez-Marquez et al., 2018) used KPI relationships to deal with data uncertainty; (Cai et al., 2009) identified KPI relationships to improve supply chain performance by analyzing iterative KPI accomplishment.

 In the context of MSW management, there are no academic works that have applied statistical techniques to historical KPI datasets to identify cause-effect relationships – and then used this information to prioritize action plans within a performance measurement structure. Once this research gap has been highlighted, the next point presents the research approach followed.

3. Research approach

3.1. Research methodology and objectives

 This research identifies the main cause-effect relationships among sustainability KPIs by analyzing the evolution of the historical data. Once the meaningful relationships have been indicated, they are projected to the action plan level, and it is then possible to rank these plans and establish which should be activated first to achieve the main KPIs.

 The main research objectives are: 1) analyze the historical data collected by a set of sustainability KPIs and find sound cause-effect relationships; 2) establish which are the most important KPIs to be achieved (effect KPIs) within the KPI set; 3) establish the cause KPIs that strongly affect the effect KPIs; 4) identify the action plans that should be activated first to ensure that the effect KPIs are achieved and so save resources.

 The adopted research methodology is the case study, which is adequate for the decision-making involved in this research as it can provide answers to 'why' and 'how' (Yin, 2014). Additionally, as mentioned in other academic works (Lancaster, 2007; Leon et al., 2020), the quantitative approach taken in this research is adequate as it: 1) focuses on establishing causal relationships among

- 137 variables (KPIs); 2) and presents a study based on the application of statistical techniques (PCA) to
- 138 find meaningful relationships among KPIs.
- 139 *3.2. Methodology*
- 140 Figure 1 shows the methodology developed for this research; the main steps are the following:
- 141 Expert group definition.
- 142 KPIs and action plan selection.
- 143 Data matrix.
- 144 Data analysis.
- 145 Results discussion.

147 Figure 1. Research methodology

148 This is a sequential methodology, where the outputs of one phase are the inputs of the following

149 phase (as presented below).

150 Phase 1. Expert group definition

151 An expert group is formed of the decision-makers who conduct the phases of the next methodology.

152 The expert group should be both multi-disciplinary and experienced in waste management and 153 performance measurement, mainly dealing with the definition of strategic objectives, KPIs, and 154 action plans.

155 Phase 2. KPIs and action plan selection

156 The expert group selects the KPIs and action plans of the performance structure to be included 157 within the study. The selected KPIs must: 1) have collected historical data during some of the

 previous time periods; 2) be linked to strategic objectives; 3) be grouped into the three dimensions of sustainability: economic (E), social (S), and environmental (ENV).

160 Phase 3. Data matrix

 The data matrix includes the study variables (KPIs) in columns and observations in rows. Each intersection of this matrix contains the historical value of the KPI, which was collected within the period of observation. Additionally, since it is highly likely that KPIs have different collection frequencies, it is necessary to choose a common frequency and bring all the values to that frequency. For instance, the data coming from the KPIs in an annual analysis will be homogenized to an annual frequency, and it is necessary to apply different operations to the data of each KPI (for instance, the simple average) when its frequency is other than annual. The resulting frequency standardized matrix is then used for data analysis. Additionally, decision-makers will assess this data matrix from a global standpoint and may exclude some KPIs that do not have enough recent historical data or present irregularities.

Phase 4. Data analysis

 Once that the frequency standardized matrix has been calculated, it is possible to apply a statistic technique to identify relationships between the variables (KPIs in our case). Principal component analysis (PCA) is then applied to identify the main cause-effect among the data matrix KPIs. This technique has already proven its efficiency in analyzing the conjoint evolution of variables (KPIs) and the identification of meaningful cause-effect relationships in the context of this research – such as: the relative lack of historical observations of the variables compared with the number of variables; missing data in some of the time periods; and various measurement units of variables such as monetary (euros), time (minutes, hours, days, etc.) or rates (percentages) (Jackson, 2003; Rodríguez-Rodríguez et al., 2020a; Wold et al., 2001). From the application of the PCA, the expert group will be able to identify the KPIs that are maintaining meaningful cause-effect relationships over time; in other words, changes in the values of some KPIs lead to changes in the values of other KPIs. Once the correlated KPIs have been identified, the decision-makers in the expert group choose which of these KPIs are the most important (effect KPIs) from an organizational point of view

 (sustainability in this research) and then identify the main cause KPIs associated with these effect KPIs. The main steps to apply are:

- 187 Take the initial frequency standardized matrix (study variables, KPIs, in columns and observations in rows).
- 189 Apply statistical software that supports PCA analysis.
- Decide, regarding the data variability explained, how many principal components to retain for 191 the study.
- 192 Identify the KPIs that are forming each of the retained principal components.
- Define the most important KPIs to be reached (the effect KPIs).
- 194 Identify which are the KPIs (called cause KPIs) that most influence these effect KPIs.

Phase 5. Results discussion

 Based on the results achieved in the previous phase, decision-makers will be able to identify the action plans that are associated with the strategic objectives linked to both the cause-and-effect KPIs. They can then establish an activation prioritization of such action plans: firstly, the action plans associated with the strategic objectives linked to the KPIs that have more impacts on the most important effect KPIs; secondly, the action plans associated with the strategic objectives linked to the most important effect KPIs; and thirdly, the remaining action plans associated with the strategic objectives linked to other KPIs. By carrying out this activation prioritization of the action plans, decision-makers will improve the probability of achieving the values of the most important effect KPIs, as well as saving organizational resources when achieving the strategic objectives.

4. Case study

4.1. Case study description

 The case study was developed at Castelló de la Plana City Council which had just approved its local waste management plan. Castelló de la Plana is a Spanish Mediterranean city, capital of the province of Castellón, in the north of the Valencia Region, and has a population of 172,589 (INE, 2021). Waste generation in the city exceeds 1.25 kg per resident/day and waste collection is divided into five fractions (glass, packaging, paper & cardboard, biowaste, and mixed MSW) according to

 current regulations (Spain, 2022). The city also has a network of recycling centers, both fixed and mobile, for depositing specific waste either because of its volume (e.g., household appliances) or its hazardous nature (e.g., engine oils, solvents, X-ray sheets). Finally, it has a small number of specific bins for the collection of cooking oil, textiles, and batteries, respectively. With all these resources, the current separation rate at source is 15.30% by weight of the MSW managed.

 Mixed MSW is the majority fraction by weight and is deposited in 'all-in-one' containers. These are collected with a rear-loading and side-loading collection service structured in 14 daily routes. Selective biowaste collection is carried out through six routes, with alternative frequencies, and contributes 3.66% of the total municipal weight. For the selective collection of paper & cardboard, which represents 3.59% of the total by weight, the service has three top-loading and one side-loading collection trucks, as is the case with the selective collection of packaging, which contributes 2.36% of the total municipal waste weight. The average collection frequency is three days a week. The fraction with the lowest percentage by weight of the total is glass (2.27%) , whose collection is carried out with top-loading collection trucks once a fortnight.

 Regarding the main MSW fractions treatment: packaging, paper & cardboard, and glass are 227 deposited directly at the facilities of the recyclers for sorting. Mixed MSW and biowaste collected in 228 the city are deposited at the transfer plant of a provincial public company that manages the treatment and valorization of these fractions (covering 63% of the province's population). In this plant, bulky and improperly disposed of waste in containers is separated and the rest is compacted for transport to a composting plant. Once the waste arrives in the composting plant, the usual mechanical and biological treatments are carried out. MSW is subjected to various mechanical treatments for the recovery of metals, plastics, paper, etc. The remaining organic matter and biowaste that are collected selectively are aerobically processed through fermentation, maturation, and refining. Due to the age of the facilities, the current rejection rate is near 75% (Reciplasa, 2023) and the final destination is a controlled landfill.

4.2. Case study development

Phase 1. Expert group definition

 To apply the methodology, a group of experts was created that included: three senior managers (one from each of the three main MSW management companies in Eastern Spain); two municipal engineers; a PhD engineer from the Universitat Jaume I; two PhDs engineers from the Universitat Politècnica de València; two local political representatives; and four environmental educators from the provincial MSW management board. All decisions were made consensually.

244 The expert group had four face-to-face meetings within a period of three months.

245 Phase 2. KPIs and action plan selection

246 From a performance measurement perspective, the Castelló de la Plana City Council had defined 247 the following elements in its 2022 local waste management plan (Ajuntament de Castelló, 2022):

- 248 36 strategic objectives.
- 249 98 action plans
- 250 36 KPIs.

 An informative meeting was first held with the experts to gather data. The main objective was to obtain initial proposals for KPIs and group them into the three dimensions of sustainability. Such a proposal was written and explained by the facilitator and then emailed to the experts. Table 1 presents the description of the 36 KPIs classified into three sustainability dimensions.

year (€/res.)

256

- 257 Table 2 describes the 36 strategic objectives and their 98 associated action plans, as well as their
- 258 link to the KPIs.
- 259 The KPIs were then linked with the objectives and associated action plans shown in Table 2.

260 Table 2: KPIs, objectives, and associated action plans.

262 Phase 3. Data matrix

263 In this phase, annual data for the 36 KPIs was collected and the resulting data matrix is presented

264 in Table 3, where it is possible to observe the 36 KPIs of the study in rows, observations in columns,

265 and the historical value of these KPI for the years 2017-2022.

(€/res.)

 The historical data is a highly compact data matrix, where most the KPIs have historical data for all six years of the study. The exceptions are S5 and ENV16 – which although included in the 2022 planning, were only measured in 2017, and so the expert group decided to exclude them from the next phase of data analysis.

272 Phase 4. Data analysis

273 The PCA technique was applied to the data matrix, using SPSS v16.0 and following a rotation

274 method of Varimax normalization and Kaiser criterion. Two principal components were then retained

275 for the study as they explained 99% of the data variability – as shown in Table 4.

276 Table 4: Data variability explained by the principal components

 The two principal components retained for the study are formed by the KPIs, and it is possible to identify which of these two principal components contribute most by making a graphical analysis of the orthogonal situation of the KPIs within the two principal components (see Figure 2).

Figure 2. Graphic shows the KPI orthogonal situation within the principal components.

282 By considering the 45^o line from the origin (in green in Figure 2), it is possible to classify an orthogonal distribution of the KPIs into one of the two principal components depending on which principal component is closest. Figure 2 shows how the variables (KPIs) are graphically situated within two principal components: PC1 on the x-axis and PC2 on the y-axis. Each KPI contributes to the formation of the principal components, but they can be classified as more related to one of the principal components than to another depending on the graphical proximity. Two green lines have been added to the graph to make it easier to understand to which principal component each KPI is closest:

- Principal component 1 (x-axis): E2, E3, E4, E5, E8, E9, E10, E11, S2, S3, S4, ENV5, ENV9, ENV10, ENV11, ENV13, ENV14, ENV15.
- Principal component 2 (y-axis): E1, E6, E7, E12, E13, S1, S6, S7, ENV1, ENV2, ENV3, ENV4, ENV6, ENV7, ENV8, ENV12.

 The expert group used its experience and knowledge of the organization's waste management process (past and present) to identify which of the effect KPIs are most important:

- E6: This KPI represents the cost of the mixed waste disposal service per resident and year expressed in €/res. These costs include labor, materials, machinery, and indirect costs of the disposal plant for one year. Once the total cost has been obtained, it is divided by the population registered in the municipality for the year of measurement.
- S1: This KPI represents the number of people participating in each of the environmental awareness campaigns carried out in the city during a year.
- S3: This KPI measures the annual number of complaints received by the council regarding waste management (location, quantity, cleanliness and maintenance of containers, transit of the vehicle fleet, uncontrolled dumping, recycling center services, etc.).
- ENV1: This KPI represents the annual amount of $CO²$ emissions (kgs) emitted by the collection services per resident. It is calculated from the sum of emissions (produced by the fractions of mixed waste, biowaste, packaging, paper & cardboard, and glass) and divided by the total population.
- ENV2: This KPI refers to the total volume of fresh clean water used by the waste collection service for cleaning containers and vehicles.
- ENV3: This KPI is the ratio obtained by dividing the annual amount of biowaste collected by the total annual amount of containerized waste collected (mixed waste, biowaste, packaging, paper & cardboard and glass).
- ENV14: This KPI is the ratio obtained from the number of complete (all waste fractions) containerized areas with respect to the total number of points on the public road with single containers (biowaste, packaging, paper & cardboard, and glass).

 Once this is done, it is time to identify the main cause KPIs associated with the effect KPIs. Figure 2 shows the symmetric position of the KPIs with respect to the axes and so reveals the groups of KPIs with a higher cause-effect correlation (Jackson, 2003). For the effect KPIs, Table 5 shows the meaningful relationships between KPIs (in columns) and the seven identified effect KPIs and the main cause KPIs (in rows). This Table has been derived by following analytical procedures. Based on the results shown in the previous figure, and following the PCA basis, it is possible to identify the variables that are maintaining some meaningful relationships over time. These variables are those 324 that are grouped around a principal component standing directly together and symmetrically. For

325 instance, regarding the KPI E6 (column 'Effect KPI E6' in Table 5), which is defined as one of the

326 most important KPIs, the KPIs that are closest graphically are:

327 • Directly: E1, E7, E8, E12, E13, S1, S6, ENV1, ENV2, ENV3 and ENV4.

328 • Symmetrically: S7 and ENV12.

329 Table 5. Cause-effect relationships between KPIs.

330

 The relationships established above show that E8 is the KPI cause with the greatest influence (influencing all seven effect KPIs). After this, the following KPI causes stand out: E1, E7, E12, E13, S6, S7, ENV3 and ENV12, as well as those which influence five effect KPIs (E6, S1, ENV1, ENV2, ENV3). There is a group of KPIs (E6, S1, ENV1, ENV2, ENV4) that influences four effect KPIs and another group of KPIs (E2, E3, E4, E5, E9, E10, S2, S4, ENV5, ENV10, ENV11, ENV13) that influence two effect KPIs. The following phase establishes specific organizational recommendations that arise from this data analysis.

338 Phase 5. Results discussion

 Based on the results achieved in the previous phase, decision-makers were able to identify the action plans that are associated with the strategic objectives linked to both the cause-and-effect KPIs. From analyzing the results of Table 5, the cause KPIs are ranked from more to less influence (measuring this influence as the number of effect KPIs they influence). E8 is the most influential cause KPI, as it influences all seven effect KPIs. This means that the three action plans that are associated with the strategic objective that E8 is measuring (namely, 'do not exceed in five years a 15% increase in the annual cost of maintenance and cleaning of containers for this fraction in 2022') should be activated first, as these action plans will contribute to reaching the strategic objective – as well as those associated with the effect KPIs that E8 is directly affecting:

348 • E6: cost of the mixed waste disposal service per resident and year.

- 349 S1: number of people participating in campaigns per year.
- 350 S3: number of complaints received per year.
- 351 ENV1: collection service emissions per year.
- 352 ENV2: annual water footprint of the waste collection service.

360 the cause KPIs. These plans are then prioritized in the order of activation.

- 353 ENV3: selective collection of biowaste percentage with respect to total household waste.
- 354 ENV14: percentage of complete contribution areas with all the fractions with respect to the 355 total number of collection areas.

 Table 6 shows the action plan prioritization produced when carrying out this analysis for all the identified cause KPIs. Table 6 also shows the main KPI causes identified (E8, E1, E7, E12, E13, S6, S7, ENV3 and ENV12), the KPIs they affect (from the seven identified in the previous phase as the most important to be achieved), and the 25 action plans associated with the strategic objectives of

361 Table 6: Action plan prioritization

363 Decision-makers will then have available a prioritization of action plans for the whole performance

364 system that have practical and theoretical implications.

365 Practical implications

 The main aim of any performance measurement system is to ensure that the defined strategic objectives are reached in the most efficient way. The proposed methodology provides a novel and efficient approach for MSW decision-makers because it identifies – with the application of objective rather than subjective analytical procedures – the order of activation for action plans associated with strategic objectives. It enables reaching all the defined strategic objectives by activating some of the action plans in the performance measurement system and this can provide the organization with notable resource savings. However, like all performance measurement systems, this approach must consider some specific points from a practical point of view:

374 • Exogeneous variables/events and how they affect the performance measurement system in 375 the present and future. There are some interesting academic works discussing this point but the approaches are always subjective, as we do not know the future and to what extent external changes will affect future developments/performance.

 • As a result of the application of this methodology, some actions plan may not be activated. This will result in cost-savings for the organization, but it is necessary to ensure that all the defined strategic objectives for the period (usually one year) are reached despite the activation of fewer action plans. Otherwise, the application of this methodology will mean that an organization achieves short-term cost savings, but compromises the achievement of other sustainability strategic objectives.

384 • Additionally, it is necessary to keep in mind that an effective follow-up should be carried out in the short-term to ensure that the activation of these analytically chosen action plans is truly helping achieve all the defined strategic objectives of the performance measurement system. The application of this methodology provided the Castelló de la Plana city council with an order of activation for its 98 action plans. The council was recommended to first activate the 25 action plans associated with the strategic objectives of the cause KPIs. This will make it possible to achieve the meta values of the cause KPIs they are associated with for strategic objectives – as well as those associated with the effect KPIs. With the initial activation of these 25 action plans, the city council can later check whether it is achieving the meta values of both cause-and-effect KPIs. If so, it would not need to activate the action plans associated with the strategic objectives of the effect KPIs (whose estimated cost is €3.2m for 2022) and the funds could be used elsewhere within the city council. If it is necessary to activate some of the action plans associated with the strategic objectives of the effect KPIs, the council would still save some money if it does not need to activate all of the plans. Therefore, the activation times of the action plans should follow Table 6 and have control and check points.

Theoretical implications

 It is well known that numerous aspects (operational, economic, environmental, and social) should be considered for the optimization of MSW systems from collection to ultimate disposal (Teixeira et al., 2014). KPIs are an important tool for evaluating performance, but they provide only partial productivity measurements. Without an appropriate aggregation metric, an analysis of KPIs may result in misleading conclusions about MSW service performance (Ferreira et al., 2020). For this

 reason, standardized methods – such as life cycle assessment (Feiz et al., 2020), life cycle costing, cost-benefit analysis, risk assessment, eco-efficiency analysis, and social life cycle cost (Allesch & Brunner, 2014) – have frequently been used. In addition to these standardized methods, multi-criteria analysis has become increasingly used in recent years (Andrade Arteaga et al., 2020; Coban et al., 2018; Habibollahzade & Houshfar, 2020) for finding relationships between performance elements. However, multiple-criteria decision analysis always harbors doubts about the subjectivity of expert opinions or about the selection of KPIs (Amaral et al., 2022).

 This case study has presented the results of applying a methodology for prioritizing waste management action plans which has proven effective in similar approaches found in the literature (Cai et al., 2009; Rodríguez-Rodríguez et al., 2020b; Sanchez-Marquez et al., 2018) and could become an efficient tool for MSW management. The methodology enables objectifying decision- making since it is based on employing historical data from a wide variety of parameters to establish cause-effect relationships using statistical analysis. Combining KPIs further removes bias in evaluation (De La Barrera et al., 2016), especially when appropriate correlations have been defined for contributing to synergistic decision-making (Papamichael et al., 2022).

 The potential limitations of this study are mainly that it is applied to just one waste management organization, and that the results of following the suggested action plan order of activation are unavailable (which would have shown to what extent the intended resource savings are produced). This is relevant because the MSW performance measurement system is multi-dimensional and, as was observed by (Parekh et al., 2015): "the performance of some indicators is influenced by the 425 performance of other indicators, similarly to how the cost of transportation does not only depend on manpower, machinery, spare vehicles but also depends on distance to landfill site, mode of operation i.e., departmental, contractual or public private partnership mode". This means that the recommended actions must always be followed up.

5. Conclusions, limitations, and future research work

 This paper has presented the results of applying a methodology to prioritize the waste management action plans of the Castelló de la Plana City Council in Spain. Such a methodology is based on the performance structure of strategic objectives, action plans, and KPIs – and their structural relationships. For the study, 36 KPIs were classified into three sustainability dimensions and six years of historical values were gathered. The main cause-effect KPI relationships were identified by applying principal component analysis, and once the most important effect KPIs were identified, the main cause KPIs were indicated. Finally, a prioritized list of 25 action plans (linked to the cause KPIs via the strategic objectives) that should be activated first (from a total of 98 action plans) was produced. Activating these plans first will ensure that their values are reached, as well as the values of the chosen effect KPIs. Following this order of activation enables the city council to save resources, as the values of the effect KPIs can be achieved without activating some (or all) of the action plans linked via the strategic objectives.

Future work could include the application of other statistical techniques to find KPI cause and effects

(such as factor analysis or partial least squares) and other implementations of the methodology to

improve and generalize its use for any MWS organization.

6. Data availability statement

- The data that supports the findings of this study are available from the corresponding author [H.M.-
- S.] on request.

7. Acknowledgments

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