

# Improving public services' performance measurement systems: applying data envelopment analysis in the big and open data context

Francesca Bartolacci, Roberto Del Gobbo and Michela Soverchia  
*Department of Economics and Law, University of Macerata, Macerata, Italy*

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## Abstract

**Purpose** – This paper contributes to the field of public services' performance measurement systems by proposing a benchmarking-based methodology that improves the effective use of big and open data in analyzing and evaluating efficiency, for supporting internal decision-making processes of public entities.

**Design/methodology/approach** – The proposed methodology uses data envelopment analysis in combination with a multivariate outlier detection algorithm—local outlier factor—to ensure the proper exploitation of the data available for efficiency evaluation in the presence of the multidimensional datasets with anomalous values that often characterize big and open data. An empirical implementation of the proposed methodology was conducted on waste management services provided in Italy.

**Findings** – The paper addresses the problem of misleading targets for entities that are erroneously deemed inefficient when applying data envelopment analysis to real-life datasets containing outliers. The proposed approach makes big and open data useful in evaluating relative efficiency, and it supports the development of performance-based strategies and policies by public entities from a data-driven public sector perspective.

**Originality/value** – Few empirical studies have explored how to make the use of big and open data more feasible for performance measurement systems in the public sector, addressing the challenges related to data quality and the need for analytical tools readily usable from a managerial perspective, given the poor diffusion of technical skills in public organizations. The paper fills this research gap by proposing a methodology that allows for exploiting the opportunities offered by big and open data for supporting internal decision-making processes within the public services context.

**Keywords** Performance measurement systems, Public services, Big data, Open data, Data envelopment analysis, Efficiency evaluation

**Paper type** Research paper

## 1. Introduction

The social and economic challenges that governments face put increasing pressure on public entities to improve services for citizens with efficient solutions while avoiding higher spending. Consequently, governments have introduced several business-inspired practices

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and tools, such as performance measurement and management (Bouckaert and Halligan, 2008; Barbato and Turri, 2017; Mwita, 2000), for a smarter government that is more efficient and closer to community needs (Criado and Gil-Garcia, 2019; Twizeyimana and Andersson, 2019). In this context, the efficient use of resources plays a crucial role in the sustainable development of public entities by directing available resources toward improving the quantity and quality of services to guarantee effectiveness and equity in meeting citizens' needs (Andrews and Entwistle, 2014; Pollitt and Bouckaert, 2011).

A performance measurement system (PMS) is defined as the processes, tools, and mechanisms used to identify objectives and support strategic processes and ongoing management through analysis, planning, measurement, and control of performance (Ferreira and Otley, 2009). Many scholars have focused on the measurement and evaluation of the efficiency of public services and the effects that business-like management practices and instruments can generate (Pawsey *et al.*, 2018), analyzing specific services, public service networks, and public entities as a whole (Agostino and Arnaboldi, 2018; Speklé and Verbeeten, 2014).

In setting up PMSs, problems concerning the nature of public services must be addressed, particularly when the lack of a competitive market makes it difficult to assess the efficiency and effectiveness of public entities, due to the absence of useful parameters to identify challenging targets. In this case, data benchmarking can play a relevant role, acting as a useful tool for comparing entities within the same field of activity, supporting the identification of challenging efficiency targets to inform feedback mechanisms, and creating a new culture of comparison as a source of learning (De Witte and Geys, 2011; Dorsch and Yasin, 1998).

Big and open data offer interesting opportunities to improve the identification of targets in contexts such as the aforementioned, as the vast amount of open information can be used to compare outputs, activities, and resources, to enable benchmarking with similar entities, and to identify the most efficient ones (Maciejewski, 2017; Rogge *et al.*, 2017). The expression "big and open data" generally refers to big data produced and released by organizations and collected as publicly available data (Roth *et al.*, 2020; Weerakkody *et al.*, 2017). These are huge amounts of information characterized by volume, variety, openness, and interoperability that can enhance the PMS and internal decision-making processes (Chen *et al.*, 2012; Kwon *et al.*, 2014; Badia and Donato, 2022).

Big and open data can also hide some challenges for their effective use. First, there is uncertainty over the quality of such datasets. Many big and open datasets have duplicate, inconsistent, and missing data, making it more difficult to generate value from their use. Accuracy problems related to data errors in (bad manual) collection and measurement processes are often reported (Sadiq and Indulska, 2017). This data quality uncertainty is a threat to the effective use of big and open data within PMSs for the improvement of efficiency processes.

Another significant challenge for big and open data in the context of public services is the lack of skills in Information and Communication Technologies (ICT) to manage the complexity of such data (Valle-Cruz, 2019; Manyika *et al.*, 2011). Analytical tools that yield readily interpretable information are, therefore, needed. These should allow managers to identify the best performers and set benchmarking targets, favoring a scientific approach that overcomes the weaknesses of a purely subjective and discretionary approach (Donthu *et al.*, 2005; Coupet *et al.*, 2021).

This paper's aim is to propose a benchmarking-based methodology that improves the feasibility of using big and open data in the efficiency evaluation of organizations providing public services, to exploit the potential of these data in supporting internal decision-making processes and to overcome the critical issues mentioned above. The proposed methodology can support policymakers and managers in defining challenging targets and assessing their performance. In particular, the study employs data envelopment analysis (DEA) in combination with a multivariate outlier detection technique—the local outlier factor (LOF) algorithm—to ensure the effective use of available information in the presence of

multidimensional datasets with anomalous data. An empirical implementation of the methodology is conducted on waste management services in Italy, for which big and open data pertaining to municipalities are available. Notwithstanding, the methodology is replicable in other kinds of public services.

The remainder of the paper is structured as follows: [Section 2](#) reviews the literature on the topics of interest, and the study's data sources and methodology are described in [Section 3](#). [Section 4](#) presents and discusses the main results, and [Section 5](#) draws conclusions and possible further research development.

## 2. Literature review

The adoption and implementation of PMSs has been a leading topic related to public sector reforms undertaken in recent decades around the world ([Hood, 1995](#); [Humphrey et al., 2005](#)). New public management (NPM) has promoted PMSs because their principles and tools support economic rationality and a focus on results ([Hood, 1991](#)), although a strand of the literature highlights that NPM effects seem to be controversial, as they encourage business-inspired practices not aligned with public values, such as equity and impartiality ([Broadbent and Laughlin, 1998](#); [Brignall and Modell, 2000](#); [Bejerot and Hasselbladh, 2013](#)). However, there is unquestionably a need to measure the performance of public sector organizations to provide reliable and comparable information about their operations and activities, to support decision-making processes, and to inform citizens and other stakeholders ([de Kool and Bekkers, 2016](#); [Steccolini et al., 2020](#); [Melo and Mota, 2020](#)).

In particular, the topic of efficiency measurement and evaluation related to the provision of public services has been widely explored in the literature due to the growing demand for quantity and quality, together with the scarcity of financial resources. In fact, the amount of dedicated resources can hardly be increased, as raising taxes and public debt beyond a certain level is neither appropriate nor politically convenient. This represents one of the more relevant reasons for the great attention paid to the proper functioning of the PMSs of entities that provide public services ([Benito et al., 2019](#); [Lo Storto, 2016](#)). This has entailed the growing use of quantitative techniques to determine the efficiency of public utilities, the premise of services' delivery improvement, and thus public value creation ([Bannister and Connolly, 2014](#); [Elston et al., 2018](#); [Worthington, 2000](#)).

Big and open data can improve the efficiency measurement and performance management of public organizations. Although the literature on the potential that big and open data can offer to public value creation is quite rich ([Ruijter et al., 2023](#); [Zuiderwijk and Janssen, 2014](#)), it essentially focuses on open government issues. Scholars have examined aspects such as public entities' transparency and accountability toward the community, as well as citizens' involvement in providing new services to better respond to their needs ([Schmidhuber et al., 2019](#); [Hitz-Gamper et al., 2019](#)), thus focusing on the external impact of the use of such data. Conversely, the topic of how big and open data can influence internal decision-making processes in public entities, thereby sustaining the definition of public strategies and programs, is very scarcely explored. According to the OECD ([Van Ooijen et al., 2019](#)), this is an important area of application and development of big and open data that can become an essential source of information for supporting the performance measurement of public organizations to pursue efficiency and effectiveness ([Rogge et al., 2017](#)). These data can be employed to support data benchmarking, increasing both the number of entities compared and the information on the inputs and outputs of their processes ([Song et al., 2017](#)).

Big and open data also present limitations and challenges ([Boyd and Crawford, 2012](#); [Picazo-Vela et al., 2012](#)). Some scholars identify two broad categories of critical issues: "privacy-related problems" and "technical difficulties" ([Desouza and Jacob, 2017](#)). In the context of the public sector, the latter are exacerbated by the poor diffusion of technical capabilities that are

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necessary to fully exploit big and open data (Grundke *et al.*, 2018). For the same reason, the ability to process vast amounts of data is a critical challenge for many local entities (Mergel *et al.*, 2016). Therefore, analytical tools that are understandable from a managerial view should be available to public managers to help them extract value from data and improve the PMS (OECD, 2019). Thus, the literature proposes several applications of DEA in the big and open data context to evaluate the relative efficiency of a vast group of entities called decision-making units (DMUs) in the case of multiple input and multiple output processes (Chen and Jia, 2017; Chu *et al.*, 2018; Badieezadeh *et al.*, 2018). Some of these applications also occur in the public sector, particularly in the field of environmental issues (Zhu, 2022).

The use of big and open data poses a further issue related to the quality of the dataset. Data quality dimensions, such as accuracy, completeness, and consistency, are a fundamental notion in performance measurement processes based on big and open data. As the issue of performance measurement is often not considered when big and open data are originally produced and collected (Sadiq and Indulska, 2017), the quality of huge amounts of data flowing across different data sources can become a problem. Users deal with unexplored and large datasets that potentially contain incorrect, incomplete, and inconsistent data or those lacking integrity. These can generate misleading performance evaluations and, thus, decisions with undesirable impacts or negative consequences for the community (OECD, 2015). This issue is especially critical for data-driven benchmarking, such as DEA benchmarking, because the presence of outliers in the reference set can compromise the identification of inefficient entities and the subsequent assignment of improvement targets (Johnson and McGinnis, 2008). In other words, only if the data quality condition is satisfied can DEA be correctly used to define inefficient operating entities and calculate the efficiency gap, enabling policymakers to develop performance-based public policies aimed at improving the results of both single public organizations and the public sector as a whole (Guerrini *et al.*, 2015).

The literature provides a wide range of techniques for assessing and improving the quality of data. Most of these are analyzed in the context of mathematical-statistical studies and aim to identify possible data quality errors by detecting the records of datasets that can be considered outliers (Batini *et al.*, 2009). Outlier detection is the focus of several review papers that highlight the advantages and limitations of various techniques (Markou and Singh, 2003a, b; Hodge and Austin, 2004). These are distinguished by several criteria, such as the dimension of the feature space (one or multiple), the data distribution (known or unknown), the range of surrounding data points (global or local), and the data labels (present or absent). Among these techniques, local outlier algorithms, such as the LOF, are especially suitable for real-world and multidimensional datasets characterized by variable densities, no *a priori* knowledge of the data distribution, and no labeled data, all features that are very frequent in the context of big and open data (Smiti, 2020; Alghushairy *et al.*, 2021). To the best of our knowledge, no empirical studies have applied these algorithms in the context of big and open data.

In summary, the relevant literature highlights an important gap that this paper aims to address. The opportunities of big and open data for PMSs in the public sector are still largely unrealized (Jensen *et al.*, 2023; European Commission, 2022; Van Ooijen *et al.*, 2019), and empirical research proposing practices on how public organizations can handle big and open data to support internal decision-making processes is needed. In particular, very few empirical studies have explored how to make the use of big and open data more feasible for this purpose (Rogge *et al.*, 2017; Di Vaio *et al.*, 2022; Abuljadail *et al.*, 2023), overcoming the constraints related to data quality and the need for analytical tools that are readily usable from a managerial perspective, given the poor diffusion of technical skills in public organizations (Sadiq and Indulska, 2017; Weerakkody *et al.*, 2017; OECD, 2019).

This paper aims to contribute to filling this gap within the strand of the literature on improving the technical features of PMSs in the public sector (Garengo and Sardi, 2021; Fryer *et al.*, 2009).

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### 3. Data and methods

#### 3.1 Methods

To achieve the research aim, a methodology that combines DEA with the LOF method was employed on a specific public utility—waste management—in the context of the separated waste collection services provided in Italy, for which big and open data are made available from the Italian Institute for Environmental Protection and Research (ISPRA).

The research protocol can be summarized in the following three consequential steps: (1) the entities are grouped into homogeneous subgroups to control for environmental heterogeneity (on the basis of the available data, the most suitable exogenous variables are chosen); (2) taking into account the peculiarities of big and open data, the LOF algorithm is applied within each subgroup, to identify and remove local outlier; and (3) within each subgroup, DEA is applied for the remaining entities to calculate the efficiency scores and the targets to be assigned. To evaluate the advantage obtainable from this procedure, in terms of more achievable targets, steps 1 and 3 can be applied again without step 2 (identifying and removing the outliers), comparing the targets thus obtained with those previously calculated with the described procedure.

To realize the first step, the data retrieved from the ISPRA database related to DMUs (the municipalities) were grouped into homogeneous subgroups to control for environmental heterogeneity (Charnes *et al.*, 1981). In many real-life applications, non-homogeneity is common among DMUs due to diverse environmental variables, so efficiency evaluation must deal with these misleading differences to avoid bias (Dyson *et al.*, 2001). Splitting the set of DMUs into multiple groups allows each DMU to be evaluated against only true peers, that is, those whose environmental contexts are similar to its own (Cook *et al.*, 2015). This solution is very intuitive compared to others proposed for controlling environmental heterogeneity (Sarra *et al.*, 2017; Fried *et al.*, 2002), and it is therefore effective from a managerial point of view.

The second step of the methodology was to apply an outlier detection technique to each subgroup of municipalities. Although outlier detection is not a negligible step in data analysis, in many articles on DEA applications in a real “big and open data” environment, the issue of outliers or techniques used to identify them often does not emerge explicitly (Chen and Jia, 2017; Chu *et al.*, 2018; Zhu *et al.*, 2017). Given the practical significance of treating outliers in DEA-based benchmarking, the proposed methodology emphasizes the use of a technique specifically suitable for certain characteristics of datasets in a “big and open data” context, such as variable densities, missing data, or data errors (Manyika *et al.*, 2011; Badiezzadeh *et al.*, 2018), and the impracticality of pre-labeling data as outliers due to the huge volume of datasets. For this reason, the LOF algorithm, an unsupervised outlier detection technique based on a local approach, was used to identify and remove outliers in each subgroup of municipalities. This algorithm does not require any assumptions about the distribution of data.

The LOF algorithm evaluates the degree of outlyingness based on the level of isolation of a data point with regard to the surrounding neighborhood. The basic idea is that the density around an outlier differs significantly from the density around its neighbors. Therefore, a data point can be considered an outlier, even if it is a short distance from an extremely dense group of neighbors. Consequently, for datasets with variable densities, the algorithm gives better results than the global approach, which may not consider such a data point an outlier. To understand how to calculate the LOF, the following three key concepts are needed:

*k*-distance (*A*): The distance between point *A* and its *k*-th nearest neighbor. The *k*-distance neighborhood, denoted by  $N_k(A)$ , includes a set of points that lie in or on the circle of radius *k*-distance, centered on point *A*. The size of  $N_k(A)$  is always equal to or greater than *k* (if two or more neighbors are at the same distance from *A*).

*Reachability distance*  $RD(A, X_j)$ : The maximum between the  $k$ -distance of point  $A$  and the distance between  $A$  and another point  $X_j$ . If point  $X_j$  lies within the  $k$ -neighborhood of  $A$ , the reachability distance will be the  $k$ -distance of  $A$ ; otherwise, it will be the distance between  $A$  and  $X_j$ .

*Local reachability density*  $LRD(A)$ : inverse of the average reachability distance of  $A$  from its neighbors ( $X_i$  belonging to  $N_k(A)$  with  $i = 1, \dots, k$ ).

Based on these concepts, the LOF can be obtained using the following equation:

$$LOF_k(A) = \frac{\sum_{X_i \in N_k(A)} \frac{LRD_k(X_i)}{LRD_k(A)}}{|N_k(A)|}$$

where

$k$  = number of nearest neighbors of point  $A$  (defined by the analyst)

$N_k(A)$  = set of nearest neighbors of point  $A$  ( $X_i, i = 1, \dots, k$ )

$|N_k(A)|$  = size of the local neighborhood of point  $A$

$LRD_k(X_i)$  = local reachability density of point  $X_i$  from its  $k$ -neighbors

$LRD_k(A)$  = local reachability density of point  $A$  from its  $k$ -neighbors

$LOF_k(A)$  expresses the degree to which point  $A$  can be considered a local outlier. A value nearly equal to 1 indicates that point  $A$  has a density similar to that of its neighbors and thus is not an anomalous point, whereas values significantly larger than 1 indicate a higher likelihood of outlyingness. The empirical cumulative distribution function of LOF values can be used to suggest a cutoff value above which a DMU is deemed an outlier. In fact, as noted in the literature (Coles *et al.*, 2001; Li *et al.*, 2022), the LOF values with the highest cumulative probabilities at which the increase in the frequency of individual values levels off can be considered "rare events" in the dataset (Pokrajac *et al.*, 2007). Hence, DMUs with LOF values at which the empirical cumulative distribution function flattens out (generally corresponding to a cumulative probability above 95%) can be removed as outliers.

In the third step, efficiency measurement and the consequent assigning of targets were conducted by applying DEA for the remaining DMUs in each subgroup. Regarding the efficiency concept, a classic definition of economic efficiency was employed, that is, the relationship between the costs of the inputs used and the outputs obtained (Pollitt and Bouckaert, 2011; Andrews and Entwistle, 2014). Since the efficiency objective is to minimize the input for a given level of output, an input-oriented DEA model was used to calculate the scores (Coelli *et al.*, 2005). This model, assuming variable returns to scale (VRS), can be expressed in a dual form as follows:

$$\min \varnothing_k - \varepsilon \left( \sum_{r=1}^s s_r \sum_{i=1}^m s_i \right)$$

subject to

$$y_{rk} - \sum_{j=1}^n \lambda_j y_{rj} + s_r = 0 \quad r = 1, \dots, s$$

$$\varnothing_k x_{ij} - \sum_{j=1}^n \lambda_j x_{ij} + s_i = 0 \quad i = 1, \dots, m$$

$$\sum_{j=1}^n \lambda_j = 1$$

$$\lambda_j, s_r, s_i \geq 0 \quad \forall j = 1, \dots, n; r = 1, \dots, s; i = \dots, m$$

where

$x_{ij}$  = quantity of input  $i$  consumed by the  $j$ -th DMU

$y_{rj}$  = quantity of output  $r$  produced by the  $j$ -th DMU

$\lambda_j$  = weights of outputs and inputs of the  $j$ -th DMU

$s_i$  = input slacks

$s_r$  = output slacks

$\varepsilon$  = non-Archimedean value (smaller than any positive real number and greater than 0)

DMU  $k$  is efficient if and only if  $\theta_k = 1$  and all slacks are zero. Due to the removal of outliers in the previous step, the efficiency scores generated by the model are not influenced by anomalous data and enable the obtaining of achievable targets for inefficient units. To highlight the usefulness of applying a local outlier detection technique in combination with DEA to define adequate targets for DMUs, the values resulting from this last step were compared with those obtained with the application of DEA without removing outliers.

### 3.2 Research setting and data

As specified above, the proposed methodology was employed on separated waste collection services provided in Italy, for which big and open data are available. In Italy, municipalities are responsible for services and activities connected to waste management (collection, transportation, and treatment). They may manage these services directly or outsource them to companies often owned by the same municipalities; however, the service remains public, as the overall responsibility and objectives pursued lie with the municipalities.

Data were retrieved from the ISPRA website, which collects and organizes information acquired and processed by entities involved in waste management services that must answer a questionnaire and fill out a specific form composed of various columns and sections. Therefore, missing data or entry errors may occur, meaning that the ISPRA dataset, which pertains to all Italian municipalities and is made available for anyone interested, is user-dependent (Price and Shanks, 2005).

The dataset retrieved from ISPRA comprised 3,205 municipalities, all for which disaggregated data were available on separated waste collection costs (SWCC), treatment and recycling costs (TRC), and the volume of separated waste collection (SWC). The municipalities were grouped according to two segmentation variables: (1) geographical location, defined with respect to the three macro-areas of Italy (north, center, and south), and (2) population density, adjusted to account for incoming tourist flow. For each municipality, data on the arrival of nonresidents were collected from the website of the Italian National Institute of Statistics (ISTAT). These two items, often cited in the literature as exogenous variables that may influence the efficiency of waste management services (Bosch *et al.*, 2000; Benito *et al.*, 2019), effectively control for environmental heterogeneity in the Italian context, enabling the detection of major differences in local operational conditions between municipalities. By crossing the two segmentation variables, 12 clusters of municipalities were obtained (3 macro-areas  $\times$  4 quartiles of adjusted population density), as shown in Table 1.

SWCC and TRC were considered inputs, and the total volume of SWC was considered output (Worthington and Dollery, 2001; De Jaeger *et al.*, 2011; Sarra *et al.*, 2017; Romano and Molinos-Senante, 2020). The data were normalized to take into account the number of inhabitants in each municipality, thus eliminating the size effect.

#### 4. Results and discussion

To demonstrate the relevance of the proposed methodology, DEA was first applied to each subgroup of municipalities without removing outliers. The input-oriented DEA model based on VRS was solved using DEA Frontier™ software. Having already normalized the cost values by the number of inhabitants and having used the population density as a variable for grouping the municipalities, the assumption of VRS allows to implicitly take into account additional factors that influence the scale efficiency (e.g. the size of the municipality's area) and to concentrate on technical efficiency. Table 2 reports the DEA results; notably, the percentage of municipalities with low efficiency scores was very high in each cluster (Zhu, 2000), as highlighted in the last line of the table.

If the measurement and control system took these scores into account to identify future objectives, many municipalities would be assigned very high goals, which could be excessively demanding. Table 3 shows the percentage of DMUs in each cluster that should achieve an improvement in their performance through the reduction of both inputs (SWCC and TRC) by more than 50%. For example, in cluster North-2, almost all municipalities should at least halve their costs: 87.8% for SWCC and 83.6% for TRC. In absolute terms, this means that, on average, each of these municipalities should reduce SWCC by 110,429 euros per year (on an average current value of around 150,000 euros) and transport costs by 46,470 euros per year (on an average current value of around 62,000 euros).

The high percentages may result from the existence of outliers that can be visualized with a 3D scatterplot in which the  $x$  and  $y$  axes represent the SWCC and TRC inputs, respectively, while the  $z$  axis represents the SWC output. In Figure 1, the North-2 cluster (geographical area north, population density 2nd quartile) is presented as an example. Some municipalities have completely anomalous values very far from the point cloud (red circle), whereas others are located in a region of space with low density compared to that of their neighbors (blue circle). Nevertheless, these points may not be considered outliers by the global approach.

To detect outliers, the value of  $k$  in the LOF algorithm was set to 10, that is, the minimum value to remove unwanted statistical fluctuations in the results (Breunig *et al.*, 2000), and the LOF value corresponding to 95% of the empirical cumulative distribution was considered the threshold. Table 4 shows the number of DMUs indicated as benchmarks in each cluster that may be considered outliers, presenting anomalous values.

|   |        |  |
|---|--------|--|
| Geographical location: macro-areas  | North  | Valle D'Aosta, Piedmont, Liguria, Lombardy, Emilia-Romagna, Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia |
|   | Center | Tuscany, Umbria, Marche, Lazio   |
|   | South  | Abruzzo, Molise, Campania, Apulia, Basilicata, Calabria, Sicily, Sardinia                                      |
| Adjusted population density: quartiles (inhabitants per km <sup>2</sup> ) | 1      | <86  |
|   | 2      | (86–226]   |
|   | 3      | (226–664]  |
|   | 4      | >664   |

**Table 1.**  
Segmentation variables

**Source(s):** Authors own work



| Efficiency score | % of municipalities |      |      |      |        |      |      |      |       |      |      |      |
|------------------|---------------------|------|------|------|--------|------|------|------|-------|------|------|------|
|                  | North               |      |      |      | Center |      |      |      | South |      |      |      |
|                  | 1                   | 2    | 3    | 4    | 1      | 2    | 3    | 4    | 1     | 2    | 3    | 4    |
| [0-0.1)          | 0.9                 | 0.2  | 0.0  | 0.0  | 0.0    | 0.8  | 0.0  | 0.0  | 2.1   | 1.0  | 0.0  | 0.0  |
| [0.1-0.2)        | 9.9                 | 4.8  | 4.7  | 1.5  | 5.4    | 4.2  | 1.2  | 0.0  | 22.4  | 25.2 | 10.9 | 20.0 |
| [0.2-0.3)        | 27.4                | 33.6 | 26.7 | 18.2 | 14.7   | 23.5 | 19.8 | 7.4  | 29.4  | 31.1 | 33.9 | 30.3 |
| [0.3-0.4)        | 25.1                | 26.9 | 28.6 | 33.1 | 14.0   | 16.8 | 14.8 | 16.7 | 16.4  | 15.5 | 19.4 | 20.0 |
| [0.4-0.5)        | 14.6                | 15.1 | 18.6 | 19.3 | 14.7   | 16.0 | 11.1 | 16.7 | 8.8   | 6.8  | 10.9 | 9.0  |
| [0.5-0.6)        | 6.4                 | 7.4  | 10.3 | 11.0 | 14.0   | 15.1 | 13.6 | 11.1 | 6.1   | 5.8  | 8.5  | 4.5  |
| [0.6-0.7)        | 4.7                 | 3.6  | 3.8  | 5.6  | 9.3    | 4.2  | 14.8 | 13.0 | 3.9   | 3.9  | 3.6  | 4.5  |
| [0.7-0.8)        | 2.9                 | 3.6  | 2.3  | 2.9  | 8.5    | 4.2  | 6.2  | 9.3  | 3.6   | 1.9  | 4.8  | 1.9  |
| [0.8-0.9)        | 2.0                 | 1.9  | 2.3  | 2.7  | 3.1    | 3.4  | 8.6  | 5.6  | 1.5   | 1.5  | 0.6  | 1.9  |
| [0.9-1)          | 1.2                 | 1.3  | 0.5  | 2.4  | 4.7    | 2.5  | 0.0  | 1.9  | 2.1   | 1.5  | 0.6  | 0.6  |
| 1                | 5.0                 | 1.7  | 2.2  | 3.4  | 11.6   | 9.2  | 9.9  | 18.5 | 3.6   | 5.8  | 6.7  | 7.1  |
| Total            | 100                 | 100  | 100  | 100  | 100    | 100  | 100  | 100  | 100   | 100  | 100  | 100  |
| <0.5             | 77.8                | 80.7 | 78.6 | 72.1 | 48.8   | 61.3 | 46.9 | 40.7 | 79.1  | 79.6 | 75.2 | 79.4 |

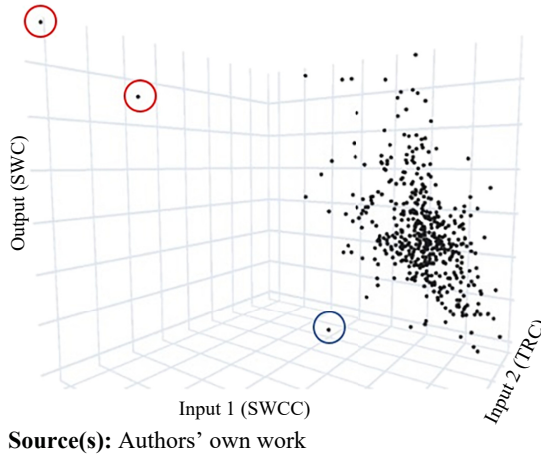
Source(s): Authors own work

**Table 2.**  
Interval distribution of  
efficiency scores for  
each cluster

| Cluster  | SWCC | % of municipalities | TRC  |
|----------|------|---------------------|------|
| North-1  | 80.2 |                     | 77.8 |
| North-2  | 87.8 |                     | 83.6 |
| North-3  | 78.7 |                     | 78.7 |
| North-4  | 73.1 |                     | 72.1 |
| Center-1 | 51.2 |                     | 48.8 |
| Center-2 | 61.3 |                     | 63.0 |
| Center-3 | 50.6 |                     | 53.1 |
| Center-4 | 42.6 |                     | 40.7 |
| South-1  | 82.7 |                     | 80.0 |
| South-2  | 81.6 |                     | 81.1 |
| South-3  | 77.0 |                     | 75.2 |
| South-4  | 79.4 |                     | 79.4 |

**Source(s):** Authors own work

**Table 3.**  
Input reductions  
greater than 50% for  
SWCC and TRC



**Figure 1.**  
3D scatterplot, cluster  
North-2

| Cluster  | Benchmark DMUs | Outliers as benchmarks | %    |
|----------|----------------|------------------------|------|
| North-1  | 17             | 10                     | 58.8 |
| North-2  | 8              | 7                      | 87.5 |
| North-3  | 12             | 8                      | 66.7 |
| North-4  | 20             | 14                     | 70.0 |
| Center-1 | 15             | 7                      | 46.7 |
| Center-2 | 11             | 5                      | 45.5 |
| Center-3 | 8              | 3                      | 37.5 |
| Center-4 | 10             | 5                      | 50.0 |
| South-1  | 12             | 8                      | 66.7 |
| South-2  | 12             | 8                      | 66.7 |
| South-3  | 11             | 7                      | 63.6 |
| South-4  | 11             | 8                      | 72.7 |

**Source(s):** Authors own work

**Table 4.**  
Outliers as  
benchmarks in each  
cluster

Removing these outliers before calculating the efficiency scores allowed the municipalities within each cluster to use more reliable benchmarks to support the identification of targets. With reference to the North-2 cluster, Table 5 shows the changes in efficiency scores in the interval distribution before and after the removal of outliers.

As shown, the percentage of municipalities with efficiency scores higher than 0.5 was more significant after the removal of outliers, rising from 19.3% to 66.3%. This means that some of the entities considered benchmarks in the first application of the DEA, having obtained an efficiency score equal to 1, were actually outliers. As already stated, the presence of these municipalities may distort the efficiency evaluation of all the others, potentially leading to incorrect performance-based political choices.

Comparing the results before and after the removal of outliers enabled evaluating the reduction in the efficiency gap, as shown in Table 6, with reference to the North-2 cluster. After the outliers were removed, the improvement targets underwent a significant decrease, as shown in Table 6. The percentage of municipalities with input reduction targets of more than 50% fell from 87.8% to 34.5% for SWCC and from 83.6% to 33.7% for TRC. Not only were these municipalities significantly reduced in number, but their targets also became more achievable, albeit still challenging, going from 110,429 to 60,800, on average, for SWCC, and from 46,470 to 23,947 for TRC.

The Kolmogorov–Smirnov test was performed for all clusters to verify the significant differences in the distribution of input reduction before and after outlier removal.

As shown in Table 7, the distances (D) between the two empirical distribution functions of input reduction before and after the removal of outliers were statistically significant for the north and south clusters. This indicates that the DMUs considered outliers were “influential observations” (Wilson, 1995), the removal of which produced relevant changes in efficiency measures. By contrast, the differences for the center clusters were not significant from a statistical point of view. Indeed, the latter clusters had higher average efficiency scores (Tables 2 and 3) and fewer outliers as benchmarks (Table 4). This means that in each center cluster, the “inlier” municipalities in the reference set were considered benchmarks by the majority of the units; therefore, the distribution of efficiency scores was not greatly affected by the removal of outliers on the efficiency frontier.

The removed outliers must be analyzed to determine whether the entities actually achieved an extraordinary performance or if it resulted from data-entry errors. Given the high cost of data checking, particularly in the case of huge amounts of data, the proposed methodology is useful in defining a prioritization for further investigation, focusing first

| Efficiency score | With outlier | % of municipalities | Without outlier |
|------------------|--------------|---------------------|-----------------|
| [0–0.1)          | 0.2          |                     | 0.0             |
| [0.1–0.2)        | 4.8          |                     | 0.0             |
| [0.2–0.3)        | 33.6         |                     | 1.0             |
| [0.3–0.4)        | 26.9         |                     | 15.6            |
| [0.4–0.5)        | 15.1         |                     | 17.1            |
| [0.5–0.6)        | 7.4          |                     | 23.2            |
| [0.6–0.7)        | 3.6          |                     | 19.4            |
| [0.7–0.8)        | 3.6          |                     | 11.5            |
| [0.8–0.9)        | 1.9          |                     | 5.4             |
| [0.9–1)          | 1.3          |                     | 3.8             |
| 1                | 1.7          |                     | 3.1             |

Source(s): Authors own work

**Table 5.**  
Interval distribution of  
efficiency score before  
and after outlier  
removal for cluster  
“North-2”

| Inputs reduction (%) | % municipalities |      |                 |      |
|----------------------|------------------|------|-----------------|------|
|                      | With outlier     |      | Without outlier |      |
|                      | SWCC             | TRC  | SWCC            | TRC  |
| 0                    | 1.7              | 1.7  | 3.1             | 3.1  |
| (0-0.1)              | 0.4              | 1.1  | 3.1             | 3.8  |
| [0.1-0.2)            | 1.1              | 1.1  | 5.1             | 5.4  |
| [0.2-0.3)            | 1.5              | 3.2  | 11.2            | 11.2 |
| [0.3-0.4)            | 1.7              | 2.9  | 19.6            | 19.6 |
| [0.4-0.5)            | 5.9              | 6.5  | 23.0            | 23.2 |
| [0.5-0.6)            | 12.2             | 15.5 | 17.6            | 17.1 |
| [0.6-0.7)            | 27.5             | 26.5 | 16.3            | 15.6 |
| [0.7-0.8)            | 41.0             | 35.5 | 1.0             | 0.8  |
| [0.8-0.9)            | 6.9              | 5.9  | 0.0             | 0.3  |
| [0.9-1)              | 0.2              | 0.2  | 0.0             | 0.0  |
| 1                    | 0.0              | 0.0  | 0.0             | 0.0  |

**Table 6.** Interval distribution of input reduction percentage for cluster North-2

**Source(s):** Authors own work

| Cluster  | D     | SWCC |                 | D     | TRC |                 |
|----------|-------|------|-----------------|-------|-----|-----------------|
|          |       |      | <i>p</i> -value |       |     | <i>p</i> -value |
| North-1  | 0.210 |      | <0.0001         | 0.193 |     | <0.0001         |
| North-2  | 0.625 |      | <0.0001         | 0.549 |     | <0.0001         |
| North-3  | 0.241 |      | <0.0001         | 0.237 |     | <0.0001         |
| North-4  | 0.404 |      | <0.0001         | 0.398 |     | <0.0001         |
| Center-1 | 0.114 |      | 0.441           | 0.079 |     | 0.864           |
| Center-2 | 0.096 |      | 0.749           | 0.061 |     | 0.992           |
| Center-3 | 0.150 |      | 0.410           | 0.160 |     | 0.329           |
| Center-4 | 0.189 |      | 0.510           | 0.223 |     | 0.303           |
| South-1  | 0.277 |      | <0.0001         | 0.244 |     | <0.0001         |
| South-2  | 0.382 |      | <0.0001         | 0.382 |     | <0.0001         |
| South-3  | 0.175 |      | 0.022           | 0.172 |     | 0.025           |
| South-4  | 0.147 |      | 0.111           | 0.176 |     | 0.031           |

**Table 7.** Kolmogorov-Smirnov tests

**Source(s):** Authors own work

on the outliers considered benchmarks, followed by those that have the highest LOF values. This examination provides a better understanding of the outliers without increasing costs and work, a crucial aspect, considering the often lacking ICT skills and resources needed to manage the complexity of these data in the context of public services.

As above mentioned, the removal of the anomalous values allows to improve the benchmarking and overall efficiency measurement processes, obtaining information that helps to identify more achievable targets. If the outlier analysis reveals that the anomalous values are due to measurement or transcription errors, such data will no longer be considered. Only if this analysis shows that such values are due to real virtuous cases, these extraordinary entities should be thoroughly analyzed to understand which management decisions and conditions have favored the achievement of excellent results, in order to evaluate the opportunity to import such good practices. This could support the setting of challenging medium and long-term goals that have the important advantage of not being determined subjectively, representing the arrival point of a path that probably entails improvements in organizational and management processes.

Our results highlight how this methodology can produce a significant improvement in public service PMSs. Applying DEA in combination with the LOF algorithm can improve the feasibility of using big and open data to support the internal decision-making processes of public organizations, overcoming the critical issues related to both data quality uncertainty and the need for analytical tools, yielding readily interpretable information from a managerial perspective.

As demonstrated by the results, the proposed methodology effectively addresses the problem of unrealistic targets assigned to entities that may have been erroneously considered inefficient due to the presence of outliers, as frequently encountered in real-world datasets. This problem hinders the exploitation of the opportunities offered by big and open data for the relative efficiency evaluation and benchmarking processes in the public sector, making such opportunities essentially unrealizable (Van Ooijen *et al.*, 2019). The described procedure represents a practical method for managing data quality uncertainty and therefore taking advantage of the potential of big and open data in allowing the comparison of efficiency results among a very large number of public organizations, both at the central and local levels (Rogge *et al.*, 2017). Further, it offers managers and local policymakers an intuitive and cheap methodology—a simple procedure even for small organizations—that allows them to meet the challenge concerning the need for reliable and easily usable tools for measurement and management purposes, given the poor diffusion of ICT capabilities in the public sector (Manyika *et al.*, 2011). For these reasons, the proposed methodology contributes to defining good practices on how public organizations can handle big and open data for improving PMS and can be used to carry out further empirical studies within the analyzed topic that remain scarce, as the literature shows (Garengo and Sardi, 2021).

## 5. Conclusions

This paper proposes a methodology to improve the PMSs of entities that provide public services by exploiting the potentialities offered by big and open data, with a particular focus on the proper target setting of economic efficiency. Combining DEA with LOF, the procedure described allows for addressing some of the most relevant challenges that big and open data present when used for internal decision-making processes, thereby improving the feasibility of their use within PMSs. This paper thus aims to contribute to that strand of the literature focused on the technical and operational aspects of PMSs in the public sector (Agasisti *et al.*, 2020), responding to the call of previous articles that highlighted the need to propose solutions to overcome technical problems related to PMSs concerning this context, with particular reference to data quality (Fryer *et al.*, 2009).

The managerial implications of using the proposed methodology concern two different perspectives. From a micro perspective, local policymakers and managers responsible for a single entity can compare their results with those of the best-performing entities in a peer group, thus detecting the relative efficiency of their organizations. They can identify, in simple, cheap, and non-discretionary ways, the more challenging efficiency targets and, consequently, put into effect coherent new programs to achieve a more efficient allocation of resources and improve performance. This is particularly important for public services provided in a non-competitive market and can help avoid self-referentiality in target settings (Deilmann *et al.*, 2016; McAfee *et al.*, 2012). Furthermore, this is relevant because some kinds of public services are often provided by very small entities (municipalities or companies) characterized by a scarcity of financial and human resources to dedicate to such decision and evaluation processes. Applying this methodology, entities providing public services can go beyond the traditional perspective of observing results, which looks inward and backward, and they can adopt an outward and forward looking perspective. This offers a comparison with external contexts, suggesting objectives that could be attained in the future by adopting efficient management solutions that other outstanding entities have effectively implemented

(Kouzmin *et al.*, 1999; Magd and Curry, 2003). Furthermore, it is useful to recall that errors in setting targets and, thus, objectives can have several negative consequences in relation to programming activities and allocating scarce available resources. The pursuit of goals that are not actually achievable is counterproductive and puts excessive strain on an organization and its human resources.

From a macro perspective, central policymakers (national and supranational) can use the proposed methodology to improve decision processes regarding specific kinds of public services based on real data referring to the state of the art. The objectives and related regulations can take into account particular issues affecting the public service and related management questions. Furthermore, using benchmarking in the public sector can make programs and policies more accountable to citizens, as entities can inform, explain, and justify their performance and practices to citizens and other stakeholders, making the whole policy process more transparent and democratic, thus strengthening their legitimacy (Boyne *et al.*, 2009).

The proposed methodology was applied in a specific context: Italian waste management services. Future research should address the analyzed topic, applying the methodology over time and in different public sector contexts to empirically assess its potential benefits in terms of supporting managerial decisions and improving public services PMSs through the exploitation of big and open data, which will be increasingly widespread and available in the future, including for public sector entities.

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### Corresponding author

Michela Soverchia can be contacted at: [michela.soverchia@unimc.it](mailto:michela.soverchia@unimc.it)

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