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A Two-Stage Data Envelopment Analysis Approach Incorporating the Global Bounded Adjustment Measure to Evaluate the Efficiency of Medical Waste Recycling Systems with Undesirable Inputs and Outputs

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Abstract: With the ever-increasing focus on sustainable development, recycling waste and renewable use of waste products has earned immense consideration from academics and policy makers. The serious pollution, complex types, and strong infectivity of medical waste have brought serious challenges to management. Although several researchers have addressed the issue by optimizing medical waste management networks and systems, there is still a significant gap in systematically evaluating the efficiency of medical waste recycling systems. Therefore, this paper proposes a two-stage data envelopment analysis (DEA) approach that combines the virtual frontier and the global bounded adjustment measure (BAM-VF-G), considering both undesirable inputs and outputs. In the first stage, the BAM-G model is used to evaluate the efficiency of medical waste recycling systems, and the BAM-VF-G model is used to further rank super-efficient medical waste recycling systems. In the second stage, two types of efficiency decomposition models are proposed. The first type of models decompose unified efficiency into production efficiency (PE) and environment efficiency (EE). Depending upon the system structure, the second type of models decompose unified efficiency into the efficiency of the medical waste collection and transport subsystem (MWCS) and the efficiency of the medical waste treatment subsystem (MWTS). The novel approach is used to measure the efficiency of the medical waste recycling systems in China's new first-tier cities, and we find that (1) Foshan ranks the highest in efficiency, followed by Tianjin and Qingdao, with efficiency values of 0.386, 0.180, and 0.130, respectively; (2) the EE lacks resilience and fluctuated the most from 2017 to 2022; and (3) the efficiency of MWCSs has always been lower than that of MWTSs and is a critical factor inhibiting the overall efficiency of medical waste recycling systems.

Keywords: medical waste; global bounded adjusted measure; virtual frontier; efficiency decomposition

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1. Introduction

Waste, as the byproduct of human activities, is characterized by diverse types, uncertain origins, vague quantities, and high pollution levels, presenting significant risks and challenges to social development. In the face of the dual constraints of resource scarcity and environmental concerns, there is considerable attention from decision makers, companies, and academic researchers worldwide on recovering value through waste recycling and the renewable use of waste products.

Medical waste, as a distinct waste category, possesses characteristics such as high infectivity, substantial contamination, and diverse categories. Notably, hazardous wastes account for approximately 41% of the total waste volume, a proportion eight times higher than that of ordinary waste [1]. With the advancement of China's socio-economic status, improved medical insurance services, and the arrival of an aging population era, there is a gradual increase in medical demands, leading to a rise in the generation and disposal of medical waste. Over the past five years, the average annual increase in medical waste volume has been 6.2% [2]. National health, environment quality, and economic well-being are crucial considerations in any society [3]. The continual growth in medical waste production poses significant challenges to the effective management of environmental quality and sustainable resource utilization. Consequently, in-depth studies of the efficiency of medical waste recycling systems are essential to enhance medical waste management.

Numerous prior studies have concentrated on assessing the efficiency of a specific part of the medical waste recycling process. Despite this, as evidenced by the literature review in Section 2, a glaring deficiency persists in research on the evaluation of the efficiency of medical waste recycling systems. This paper endeavors to bridge this knowledge gap by utilizing a two-stage bounded adjustment measure–data envelopment analysis (BAM-DEA) approach.

The characteristics of this study are as follows:

(1) We propose a two-stage BAM-DEA model that combines the virtual frontier and the global bounded adjustment measure (BAM-VF-G) to rank the super-efficient decision units. It is the first time that a two-stage problem has been solved using the BAM-VF-G model, considering both undesirable inputs and outputs.
(2) This paper adopts a new two-stage structure considering the internal network structure: the medical waste collection and transport subsystem (MWCS) and the efficiency of the medical waste treatment subsystem (MWTS), which is helpful for distinguishing the effectiveness during different processes and can comprehensively evaluate efficiency in combination with MWCS efficiency and MWTS efficiency.
(3) The efficiency of the medical waste recycling systems in China's new first-tier cities from 2017 to 2021 is revealed, which can support relevant departments to make scientific decisions in the future.

The technical framework is illustrated in Figure 1. The framework contains three steps. The first step is preliminary preparation, which includes classical approaches, problem analysis, and data acquisition and processing. In the second step, the BAM-G model is used to calculate the efficiency of the medical waste recycling systems and further rank the efficient decision-making units (*DMUs*) using the virtual frontier. Two types of efficiency decomposition models are proposed, which decompose the unified efficiency into PE and EE and then divide recycling systems into two stages: the MWCS and the MWTS. Finally, a discussion is conducted based on the results.

The remainder of this paper is structured as follows: Section 2 reviews the literature. In Section 3, we develop a two-stage BAM-VF-G model for analyzing the efficient *DMUs*, and subsequently two types of efficiency decomposition models are proposed. Section 4 evaluates the recycling efficiency of medical waste in China's new first-tier cities from 2017 to 2021 using the proposed models. Conclusions and future research directions are provided in Section 5.

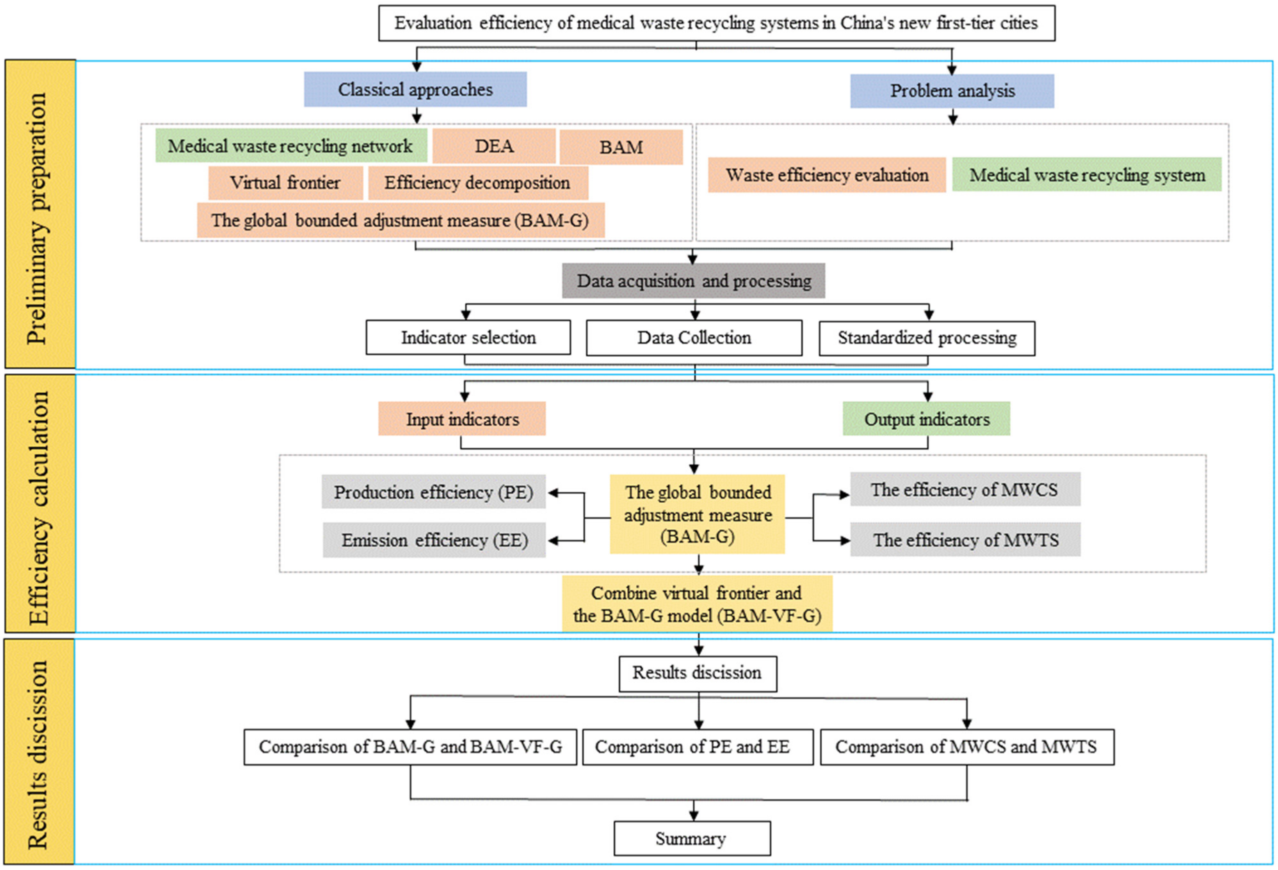

Figure 1. Technical framework of this study.

2. Literature Review

2.1. BAM

DEA, a nonparametric frontier efficiency analysis method, uses linear (and non-linear) programming techniques to assess the relative efficiency of homogeneous *DMUs*. DEA models are highly versatile, as they do not require a specific known production frontier and are well-suited for handling situations involving multiple inputs and outputs. In 1978, Chams et al. [4] introduced the first DEA model, known as the CCR model, which remains a classic in the field.

DEA models can be categorized into two groups: radial DEA and non-radial DEA models. Radial DEA models, including input-oriented, output-oriented, and non-oriented models, assume that inputs and/or outputs change proportionally. However, in many real-world scenarios, inputs like labor, energy, and capital cannot change proportionally [5]. This is where non-radial DEA comes into play, as it relaxes the assumptions of proportionality and direction, allowing for non-proportional changes in inputs and outputs, making it particularly suitable for handling undesirable outputs. Classical non-radial DEA models include the additive DEA [6], the slacks-based measure (SBM) [7], and the range-adjusted measure (RAM) [8]. While the additive DEA cannot directly generate efficiency scores, the SBM approach overcomes this limitation. However, efficiency scores calculated by SBM models may vary depending on the orientation (input-oriented or output-oriented). Non-oriented SBM models address this issue but require nonlinear programming and often need to be transformed using the Charnes–Cooper transformation [9]. The RAM approach, being a non-oriented linear programming model, can directly generate efficiency scores. However, it still has some limitations, as its parameters are composed of the extremes of inputs and outputs and it frequently results in efficiency scores ranging between 0.9 and 1, making it difficult to discriminate highly efficient *DMUs*.

To address the above issues, Cooper et al. [10] introduced the bounded adjusted measure (BAM), which takes into account lower bounds for inputs and upper bounds for outputs. This approach provides greater discriminatory power in comparison. The BAM model is a linear programming model, which makes it easy to obtain global optimal solutions. The BAM model also possesses a strong ability to differentiate *DMUs* and is suitable for production situations with economies of any scale [11]. Qin et al. [12] proposed radial and non-radial BAM-G models based on a virtual efficient frontier to investigate a specific evaluation of the energy efficiency in China's coastal areas. Table 1 summarizes the specific advantages and disadvantages of these models. In this study, we extend the BAM-VF-G model proposed by incorporating a two-stage model to evaluate the efficiency of medical waste recycling systems while considering both undesirable inputs and outputs.

Table 1. Comparison of the advantages and disadvantages of the mainstream DEA model.

	Advantages	**Disadvantages**
Radial DEA	Simple	Not suitable for dealing with undesirable variables
Additive DEA	Non-radial linear programming; allows disproportionate changes in inputs and outputs	Does not directly generate efficiency scores
SBM	Non-radial and non-linear programing; suitable for optimization and adjustment	For effective *DMUs*, the discrimination is poor
RAM	Non-oriented linear programming; easy to solve; robustness	For effective *DMUs*, the discrimination is poor
BAM	Non-radial and non-oriented linear programming; allows direct generation of efficiency scores; strong differentiation ability for *DMUs*	Computationally complex

2.2. Medical Waste Efficiency Evaluation

Medical waste recycling is crucial for ensuring public health and environmental sustainability. Both practitioners and researchers have long recognized the complexity and challenges involved in assessing the efficiency of medical waste recycling. To the best of our knowledge, research on the evaluation of medical waste recycling systems has primarily focused on specific aspects, such as the professionalism of recyclers during the classification and collection stages, the medical waste treatment equipment and disposal technology in the disposal stage, as well as the risk assessment of medical waste throughout the transportation and disposal stages.

Deress et al. [13] conducted a survey of 296 healthcare workers in 12 healthcare facilities located in a town in the Amhara Prefecture of northwestern Ethiopia. The survey utilized questionnaires and observation checklists to assess the education, attitudes, and experience of the healthcare workers. Bivariate and multivariate logistic regression analyses were performed. The findings revealed that the medical staff in the town had a low level of education, unfavorable attitudes, and limited experience. Furthermore, they lacked training in medical waste management, which presented a significant barrier to the effective recycling of medical waste.

Taghipour et al. [14] conducted a six-month mechanical, chemical, and biological monitoring of medical waste disinfection equipment in 10 hospitals in Iran. Chemical monitoring results showed that 38.9% of the autoclaves examined had operational problems with pre-vacuuming, air leakage, insufficient steam penetration into the waste, and/or vacuum pumps. Biological indicators showed that about 55.55% of the samples were positive. Most applications are equipped with equipment that is not suitable for handling anatomical, pharmaceutical, cytotoxic, and chemical wastes.

Tang et al. [15] developed an integrated model to evaluate COVID-19 medical waste transportation risk by integrating an extended type-2 fuzzy total interpretive structural model (TISM) with a Bayesian network (BN). Taking the transportation process of medical waste in Nanjing as an example, the results show that insufficient personal protection of employees is a crucial risk factor for controlling the transportation of medical waste. Wang [16] used the groundwater flow model software Visual Modflow 4.2 to construct a numerical simulation model of groundwater flow. The study aimed to determine the diffusion of leachate pollutants by analyzing their migration in different spatial locations and at various time intervals. This analysis allowed for an accurate assessment of the pollutants' impact on the groundwater environment. Liu et al. [17] used life cycle assessment to determine the economic, environmental, and health and safety benefits of medical plastic waste recycling in China. A logistics model for medical plastic waste recycling in China was established, the output range of medical plastic waste by 2050 was predicted, and the benefits and costs of the medical plastic waste recycling system were evaluated under three scenarios: low, medium, and high. Through the analysis of sensitive factors, it was found that the recycling method used for medical plastics is an important factor restricting their recycling. Al-Sulbi et al. [18] proposed a method based on the fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method to rank medical waste management and proved the effectiveness of the method by comparing it with the analytic hierarchy process (AHP). The results showed that recycling was the most advantageous option. Chemical treatment, incineration, and landfills rank low due to their higher environmental and financial costs. Dwivedi et al. [19] analyzed the factors influencing third-party medical waste management and revealed the salient factors that led to the failure of the medical waste management system in India. Firstly, the causal relationship between factors was described by the unique Interval-Valued Intuitionistic Fuzzy Set of the Decision Experiment and Evaluation Laboratory. Then, the analytic network process was used to estimate the impact ranking of each factor. The results show that transportation and disposal are important factors restricting the third-party logistics management of medical waste. Ho [20] employed the fuzzy analytic hierarchy process to set the objective weights of evaluation criteria and select the optimal infectious medical waste disposal firm through calculation and sorting.

There are few studies that have evaluated the efficiency of medical waste recycling systems from a system perspective. DEA can systematically evaluate the efficiency of medical waste recycling through multiple inputs and multiple outputs, effectively distinguishing between efficiency and inefficiency *DMUs*. It not only assists inefficiency *DMUs* in identifying existing problems and deficiencies but also draws on the successful experiences of efficiency *DMUs* to guide underperforming *DMUs* in adjusting their development strategies, optimizing resource allocation, and thereby enhancing overall performance. But there is no research on the efficiency evaluation of medical waste recycling systems using the DEA method, and only some scholars have applied the DEA to evaluate the efficiency of hospital performance [21,22], which is not conducive to the advancement of medical waste recycling systems. In light of this, we propose the BAM-VF-G model, a DEA method known for its computational convenience, resilience to outliers, and capacity to yield more objective and accurate results, for evaluating the efficiency of medical waste recycling systems.

3. Methods

3.1. Problem Description

The medical waste recycling process is complex, including waste segregation and collection, primary harmless treatment, transportation, and systematic treatment [23]. It mainly includes a two-stage structure, as shown in Figure 2. In medical waste collection, the transportation subsystem (MWCS) includes the sorting and collection of medical waste, initial harmless treatment, storage, and transportation. A medical waste disposal subsystem (MWTS) includes the harmless disposal of waste, landfills, and recovery of available resources. The specific network structure is shown in Figure 3.

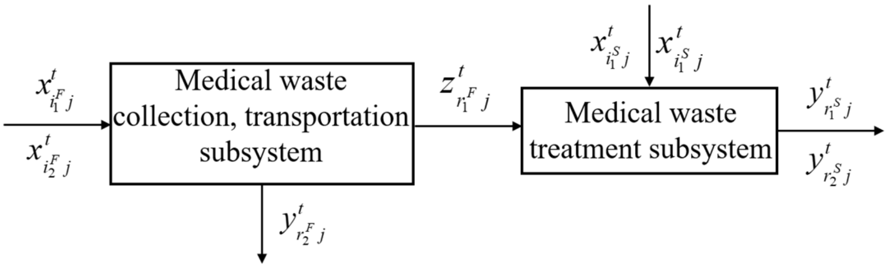

Figure 2. General two-stage network structure.

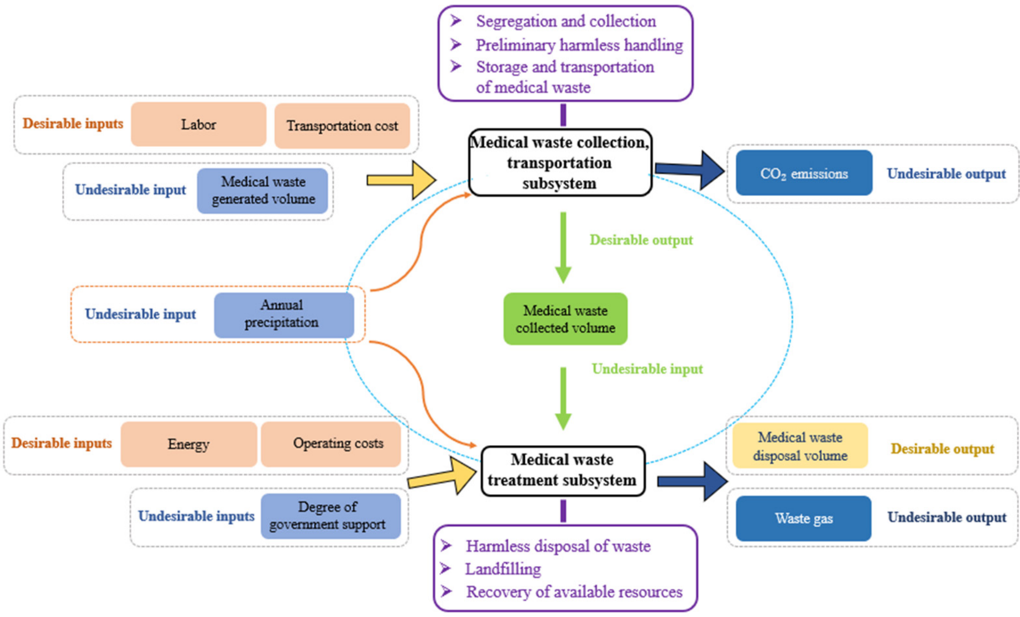

Figure 3. Concrete network model of medical waste recycling systems.

In MWCSs, inputs include two desirable inputs and two undesirable inputs, and outputs consist of one desirable output and one undesirable output. The desirable inputs are labor and transportation cost. The undesirable inputs are the medical waste generated volume and the annual precipitation [24]. The desirable output is the medical waste collected volume, and the undesirable output is CO_2 emissions. In MWTSs, inputs include two desirable inputs and two undesirable inputs, and outputs consist of one desirable output and one undesirable output. Desirable inputs include energy and operating costs. The undesirable inputs are the medical waste collected volume and the annual precipitation. In addition, government support is also considered as an undesirable input. The desirable output and undesirable output are medical waste disposal volume and waste gas, respectively. The medical waste collected volume, serving as an intermediate variable commonly referred to as a dual-role variable, can play a role either as a desirable output in MWCSs or as an undesirable input in MWTSs. Annual precipitation is considered as an undesirable input in both the MWCS and the MWTS.

3.2. Modelling Methods

3.2.1. BAM Model

A classical BAM model can be written as model (1) [10]. Suppose that there are J $DMUs$ ($DMU_j, j = 1, \ldots, J$). Each DMU utilizes I inputs to produce R outputs. Let x_{ij} ($i = 1, \ldots\ldots, I$) and y_{rj} ($r = 1, \ldots\ldots, R$) indicate inputs and outputs, respectively.

$$\begin{aligned}
& Max \sum_{i=1}^{I} B_{i0}^{t} d_{i0}^{t} + \sum_{r=1}^{R} B_{r0}^{t} d_{r0}^{t} \\
& s.t. \\
& \sum_{j=1}^{J} x_{ij}\lambda_j + d_{i0}^{t} = x_{i0} \quad i = 1, \ldots\ldots, I \\
& \sum_{j=1}^{J} y_{rj}\lambda_j - d_{r0}^{t} = y_{r0} \quad r = 1, \ldots\ldots, R \\
& \sum_{j=1}^{J} \lambda_j = 1 \quad j = 1, \ldots\ldots J \\
& d_i^t \geq 0, d_r^t \geq 0, \lambda_j \geq 0
\end{aligned} \tag{1}$$

3.2.2. BAM-G Model

To make the distance function in different periods comparable [25], based on previous studies [12,24], we extended the BAM model considering undesirable inputs and outputs using the global benchmark technology (GBT), and each DMU uses $x_{i_1 j}^t = (x_{1j}^t, x_{2j,}^t, \ldots, x_{I_1 j}^t) \in L^{I_1}{}_j$ undesirable inputs and $x_{i_2 j}^t = (x_{1j}^t, x_{2j,}^t, \ldots, x_{I_2 j}^t) \in L^{I_2}{}_j$ desirable inputs to produce $y_{r_1 j}^t = (y_{1j}^t, y_{2j,}^t, \ldots, y_{R_1 j}^t) \in L^{R_1}{}_j$ desirable outputs and $y_{r_2 j}^t = (y_{1j}^t, y_{2j,}^t, \ldots, y_{R_2 j}^t) \in L^{R_2}{}_j$ undesirable outputs, over time period t, $t = 1, \ldots\ldots T$. The production possibility set, PPS^t, can be defined as follows:

$$PPS^t = \left\{ \left(x_{i_1 j}^t, x_{i_2 j}^t, y_{r_1 j}^t, y_{r_2 j}^t \right) : \left(x_{i_1 j}^t, x_{i_2 j}^t \right) \text{can produce} \left(y_{r_1 j}^t, y_{r_2 j}^t \right) \right\} \tag{2}$$

This novel DEA model is constructed as follows:

$$
\begin{aligned}
&Max \sum_{i_1^F=1}^{I_1^F} B^t_{i_1^F 0} d^t_{i_1^F 0} + \sum_{i_2^F=1}^{I_2^F} B^t_{i_2^F 0} d^t_{i_2^F 0} + \sum_{i_1^S=1}^{I_1^S} B^t_{i_1^S 0} d^t_{i_1^S 0} + \sum_{i_2^S=1}^{I_2^S} B^t_{i_2^S 0} d^t_{i_2^S 0} \\
&+ \sum_{r_2^F=1}^{R_2^F} B^t_{r_2^F 0} d^t_{r_2^F 0} + \sum_{r_1^S=1}^{R_1^S} B^t_{r_1^S 0} d^t_{r_1^S 0} + \sum_{r_2^S=1}^{R_2^S} B^t_{r_2^S 0} d^t_{r_2^S 0} \\
&s.t. \\
&\sum_{j=1}^{J} x^t_{i_1^F} \lambda^t_j - d^t_{i_1^F 0} = x^t_{i_1^F 0} \\
&\sum_{j=1}^{J} x^t_{i_2^F} \lambda^t_j + d^t_{i_2^F 0} = x^t_{i_2^F 0} \\
&\sum_{j=1}^{J} x^t_{i_1^S} \lambda^t_j + d^t_{i_1^S 0} = x^t_{i_1^S 0} \\
&\sum_{j=1}^{J} x^t_{i_2^S} \lambda^t_j + d^t_{i_2^S 0} = x^t_{i_2^S 0} \\
&\sum_{j=1}^{J} y^t_{r_2^F} \lambda^t_j + d^t_{r_2^F 0} = y^t_{r_2^F 0} \\
&\sum_{j=1}^{J} y^t_{r_1^S} \lambda^t_j - d^t_{r_1^S 0} = y^t_{r_1^S 0} \\
&\sum_{j=1}^{J} y^t_{r_2^S} \lambda^t_j + d^t_{r_2^S 0} = y^t_{r_2^S 0} \\
&\sum_{j=1}^{J} x^t_{i_1^F} \lambda^t_j \le \overline{x}_{i_1^F} \\
&\sum_{j=1}^{J} x^t_{i_2^F} \lambda^t_j \ge \underline{x}_{i_2^F} \\
&\sum_{j=1}^{J} x^t_{i_1^S} \lambda^t_j \le \overline{x}_{i_1^S} \\
&\sum_{j=1}^{J} x^t_{i_2^S} \lambda^t_j \ge \underline{x}_{i_2^S} \\
&\sum_{j=1}^{J} y^t_{r_2^F} \lambda^t_j \ge \underline{y}_{r_2^F} \\
&\sum_{j=1}^{J} y^t_{r_1^S} \lambda^t_j \le \overline{y}_{r_1^S} \\
&\sum_{j=1}^{J} y^t_{r_2^S} \lambda^t_j \ge \underline{y}_{r_2^S} \\
&\sum_{t=1}^{T} \sum_{j=1}^{J} \lambda^t_j = 1 \\
&\lambda^t_j \ge 0, d^t_{i_1^F} \ge 0, d^t_{i_2^F} \ge 0, d^t_{i_1^S} \ge 0, d^t_{i_2^S} \ge 0, d^t_{r_2^F} \ge 0, d^t_{r_1^S} \ge 0, d^t_{r_2^S} \ge 0 \\
&j = 1, \ldots\ldots, J; i_1^F = 1, \ldots\ldots, I_1^F; i_2^F = 1, \ldots\ldots, I_2^F; i_1^S = 1, \ldots\ldots, I_1^S; \\
&i_2^S = 1, \ldots\ldots, I_2^S; r_2^F = 1, \ldots\ldots, R_2^F; r_1^S = 1, \ldots\ldots, R_1^S; r_2^S = 1, \ldots\ldots, R_2^S; \\
&t = 1, \ldots\ldots T
\end{aligned}
\tag{3}
$$

where i_1 and i_2 stand for undesirable and desirable inputs, respectively, and r_1 and r_2 represent the desirable and undesirable outputs, respectively. The total inputs are represented by $i = i_1 \cup i_2$, and the total outputs are represented by $r = r_1 \cup r_2$. i_1^F and i_2^F represent the undesirable and desirable outputs of the MWCS, and i_1^S and i_2^S represent the undesirable and desirable outputs of the MWTS. r_1^F and r_2^F represent the desirable and undesirable outputs of the MWCS; r_1^S and r_2^S represent the desirable and undesirable outputs of the MWTS; λ_j^t represents the intensity variable associated with each DMU; $d^t_{i_1}$, $d^t_{i_2}$, $d^t_{r_1}$, and $d^t_{r_2}$ are the slack variables of undesirable inputs, desirable inputs, desirable outputs, and undesirable outputs, respectively; and the subscript "0" represents the DMU to be evaluated. BAM considers lower-sided ranges for inputs and upper-sided ranges for outputs, whereas the BAM model determines bounds based on upper and lower ranges for each input and output [24]. $\underline{x}_{i_2^F}$, $\underline{x}_{i_2^S}$, $\underline{y}_{r_2^F}$, and $\underline{y}_{r_2^S}$ denote the minima among the ith desirable inputs and the rth undesirable outputs, respectively, and $\overline{x}_{i_1^F}$, $\overline{x}_{i_1^S}$, and $\overline{y}_{r_1^S}$ denote the maxima among the ith undesirable inputs and the rth desirable outputs. It is important to note that the lower-sided ranges for each desirable input and undesirable output depend only on the lower bounds of the desirable input, the undesirable output, and DMU_0. In contrast, the upper-sided ranges for each undesirable input and desirable output depend only on the upper bounds of the undesirable input, the desirable output, and the DMU_0. That is why Cooper et al. [10] called the model the BAM. Additionally, $B^t_{i_1^F}$, $B^t_{i_2^F}$, $B^t_{i_1^S}$, $B^t_{i_2^S}$, $B^t_{r_2^F}$, $B^t_{r_1^S}$, and $B^t_{r_2^S}$ are the bounds of the model. $B^t_{i_2^F}$ and $B^t_{i_2^S}$ and $B^t_{r_2^F}$ and $B^t_{r_2^S}$ depend on the lower-sided ranges for desirable inputs and undesirable outputs, respectively, whereas $B^t_{i_1^F}$, $B^t_{i_1^S}$, and $B^t_{r_1^S}$ depend on the upper-sided ranges for undesirable inputs and desirable outputs, respectively. If input i for DMU_0 satisfies $x^t_{i_2^F 0} = \underline{x}_{i_2^F}$, there is no desirable input excess. For example, the corresponding slack is zero ($d^t_{i_2^F} = 0$), and consequently $B^t_{i_2^F}$ will be zero. Similarly, if desirable output r for DMU_0 satisfies $\overline{y}_{r_1^S} = y^t_{r_1^S 0}$, there is no desirable output shortfall. For instance, the corresponding slack is zero ($d^t_{r_1^S} = 0$), and $B^t_{r_1^S}$ will be zero. These discussions have been proved by Cooper et al. (2011) [10]. In this model, $B^t_{i_1^F}$, $B^t_{i_2^F}$, $B^t_{i_1^S}$, $B^t_{i_2^S}$, $B^t_{r_2^F}$, $B^t_{r_1^S}$, and $B^t_{r_2^S}$ at DMU_0 are defined as follows:

$$
\begin{aligned}
B^t_{i_1^F 0} &= \frac{1}{\left(I_1^F+I_2^F+I_1^S+I_2^S+R_2^F+R_1^S+R_2^S\right)(\overline{x}^t_{i_1^F}-x^t_{i_1^F 0})}, \overline{x}^t_{i_1^F} = \max_j\left\{x^t_{i_1^F j}, i_1^F = 1,\ldots,I_1^F; t=1,2,\ldots,T\right\}\\
B^t_{i_2^F 0} &= \frac{1}{\left(I_1^F+I_2^F+I_1^S+I_2^S+R_2^F+R_1^S+R_2^S\right)(x^t_{i_2^F 0}-\underline{x}_{i_2^F})}, \underline{x}_{i_2^F} = \min\left\{x^t_{i_2^F}, i_2^F = 1,\ldots,I_2^F; t=1,2,\ldots,T\right\}\\
B^t_{i_1^S 0} &= \frac{1}{\left(I_1^F+I_2^F+I_1^S+I_2^S+R_2^F+R_1^S+R_2^S\right)(\overline{x}^t_{i_1^S}-x^t_{i_1^S 0})}, \overline{x}^t_{i_1^S} = \max_j\left\{x^t_{i_1^S j}, i_1^S = 1,\ldots,I_1^S; t=1,2,\ldots,T\right\}\\
B^t_{i_2^S 0} &= \frac{1}{\left(I_1^F+I_2^F+I_1^S+I_2^S+R_2^F+R_1^S+R_2^S\right)(x^t_{i_2^S 0}-\underline{x}_{i_2^S})}, \underline{x}_{i_2^S} = \min\left\{x^t_{i_2^S}, i_2^S = 1,\ldots,I_2^S; t=1,2,\ldots,T\right\}\\
B^t_{r_2^F 0} &= \frac{1}{\left(I_1^F+I_2^F+I_1^S+I_2^S+R_2^F+R_1^S+R_2^S\right)(y^t_{r_2^F 0}-\underline{y}_{r_2^F})}, \underline{y}_{r_2^F} = \min\left\{x^t_{r_2^F}, r_2^F = 1,\ldots,R_2^F; t=1,2,\ldots,T\right\}\\
B^t_{r_1^S 0} &= \frac{1}{\left(I_1^F+I_2^F+I_1^S+I_2^S+R_2^F+R_1^S+R_2^S\right)(\overline{y}_{r_1^S}-y^t_{r_1^S 0})}, \overline{y}_{r_1^S} = \max\left\{y^t_{r_1^S}, r_1^S = 1,\ldots,R_1^S; t=1,2,\ldots,T\right\}\\
B^t_{r_2^S 0} &= \frac{1}{\left(I_1^F+I_2^F+I_1^S+I_2^S+R_2^F+R_1^S+R_2^S\right)(y^t_{r_2^S 0}-\underline{y}_{r_2^S})}, \underline{y}_{r_2^S} = \min\left\{y^t_{r_2^S}, r_2^S = 1,\ldots,R_2^S; t=1,2,\ldots,T\right\}
\end{aligned}
\tag{4}
$$

3.2.3. Virtual Frontier Data Envelopment Analysis

However, the traditional BAM model is the result of a DMU comparing its production capacity with the optimal true frontier production capacity. When the input data and output data of some $DMUs$ are very close, this can result in multiple $DMUs$ having efficiency values of 1, and the BAM-G model cannot distinguish between these $DMUs$ [26,27]. To address this issue, Andersen and Petersen [28] proposed the Super DEA method. The principle behind it is to exclude the evaluated DMU_0 in which the efficient $DMUs$ have scores greater than 1, thus enabling a more refined ranking. For illustration, let us consider four $DMUs$, as shown in Table 2. When the Super DEA model evaluates DMU_B, the inputs of the reference $DMUs$ are {2,7,4} and the outputs are {7,5,3}, resulting in a reference frontier of ACD. However, when the Super DEA model evaluates DMU_D, the inputs of the reference set are {2,9,7}, and the outputs are {7,4,5}, which leads to a reference frontier of ACB. The issue here is that the reference sets and reference frontiers vary for different units being evaluated, which can result in less consistent or reasonable results.

Table 2. The example.

DMUs	Inputs	Outputs
A	2	7
B	9	4
C	7	5
D	4	3

To address the aforementioned disadvantages, the concept of virtual frontier data envelopment analysis (virtual frontier DEA) was first introduced by Bian and Xu [29]. In this model, the virtual frontier is established by adjusting inputs and outputs in a specific proportion, ensuring that the efficiency values fall between 0 and 1, unlike the traditional DEA model. As shown in Figure 4, the efficiency values of entities A, B, C, and D are all 1 in the traditional DEA model, making it unable to distinguish between them. The virtual frontier DEA, on the other hand, constructs virtual frontiers F, G, H, and I as the optimal reference frontiers for entities A, B, C, D, and E. This allows for differentiation of the efficiencies of A, B, C, D, and E, all of which are considered DEA-inefficient.

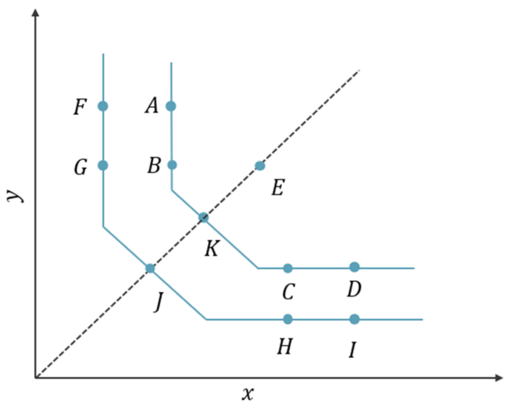

Figure 4. The principle of virtual frontier DEA.

The reference *DMU* set and the evaluated *DMU* set are two different sets in this method, and the reference *DMU* set remains unchanged so that its results may be more reasonable than those of existing models [26]. Qin et al. [12] combined the virtual frontier with BAM to further sequence the evaluation units. In this paper, we propose a two-stage DEA approach that combines the virtual frontier and the BAM-G, considering both undesirable inputs and outputs. The proposed model is as follows:

$$
\begin{aligned}
& Max \sum_{i_1^F=1}^{I_1^F} B^t_{i_1^F 0} d^t_{i_1^F 0} + \sum_{i_2^F=1}^{I_2^F} B^t_{i_2^F 0} d^t_{i_2^F 0} + \sum_{i_1^S=1}^{I_1^S} B^t_{i_1^S 0} d^t_{i_1^S 0} + \sum_{i_2^S=1}^{I_2^S} B^t_{i_2^S 0} d^t_{i_2^S 0} \\
& + \sum_{r_2^F=1}^{R_2^F} B^t_{r_2^F 0} d^t_{r_2^F 0} + \sum_{r_1^S=1}^{R_1^S} B^t_{r_1^S 0} d^t_{r_1^S 0} + \sum_{r_2^S=1}^{R_2^S} B^t_{r_2^S 0} d^t_{r_2^S 0} \\
& s.t. \\
& \sum_{j=1}^{J} XX^t_{i_1^F} \lambda^t_j - d^t_{i_1^F 0} = x^t_{i_1^F 0} \\
& \sum_{j=1}^{J} XX^t_{i_2^F} \lambda^t_j + d^t_{i_2^F 0} = x^t_{i_2^F 0} \\
& \sum_{j=1}^{J} XX^t_{i_1^S} \lambda^t_j + d^t_{i_1^S 0} = x^t_{i_1^S 0} \\
& \sum_{j=1}^{J} XX^t_{i_2^S} \lambda^t_j + d^t_{i_2^S 0} = x^t_{i_2^S 0} \\
& \sum_{j=1}^{J} YY^t_{r_2^F} \lambda^t_j + d^t_{r_2^F 0} = y^t_{r_2^F 0} \\
& \sum_{j=1}^{J} YY^t_{r_1^S} \lambda^t_j - d^t_{r_1^S 0} = y^t_{r_1^S 0} \\
& \sum_{j=1}^{J} YY^t_{r_2^S} \lambda^t_j + d^t_{r_2^S 0} = y^t_{r_2^S 0} \\
& \sum_{j=1}^{J} XX^t_{i_1^F} \lambda^t_j \le \overline{x}_{i_1^F} \\
& \sum_{j=1}^{J} XX^t_{i_2^F} \lambda^t_j \ge \underline{x}_{i_2^F} \\
& \sum_{j=1}^{J} XX^t_{i_1^S} \lambda^t_j \le \overline{x}_{i_1^S} \\
& \sum_{j=1}^{J} XX^t_{i_2^S} \lambda^t_j \ge \underline{x}_{i_2^S} \\
& \sum_{j=1}^{J} YY^t_{r_2^F} \lambda^t_j \ge \underline{y}_{r_2^F} \\
& \sum_{j=1}^{J} YY^t_{r_1^S} \lambda^t_j \le \overline{y}_{r_1^S} \\
& \sum_{j=1}^{J} YY^t_{r_2^S} \lambda^t_j \ge \underline{y}_{r_2^S} \\
& \sum_{t=1}^{T} \sum_{j=1}^{J} \lambda^t_j = 1 \\
& \lambda^t_j \ge 0, d^t_{i_1^F} \ge 0, d^t_{i_2^F} \ge 0, d^t_{i_1^S} \ge 0, d^t_{i_2^S} \ge 0, d^t_{r_2^F} \ge 0, d^t_{r_1^S} \ge 0, d^t_{r_2^S} \ge 0 \\
& j = 1, \ldots\ldots, J; i_1^F = 1, \ldots\ldots, I_1^F; i_2^F = 1, \ldots\ldots, I_2^F; i_1^S = 1, \ldots\ldots, I_1^S; \\
& i_2^S = 1, \ldots\ldots, I_2^S; r_2^F = 1, \ldots\ldots, R_2^F; r_1^S = 1, \ldots\ldots, R_1^S; r_2^S = 1, \ldots\ldots, R_2^S; \\
& t = 1, \ldots\ldots T
\end{aligned} \tag{5}
$$

Set $x^t_{i0} = \min_j \left\{ x^t_{ij} \right\}$ and $y^t_{r0} = \max_j \left\{ y^t_{rj} \right\}$, $j = 1, 2, \ldots, J$. For the reference set of DMU_j, both inputs and outputs are stochastically generated. Referring to previous studies [30], the inputs are set as $XX^t_{i0}\lambda^t_j = [0.9x^t_{i0}, x^t_{i0}]\lambda^t_j$ and the outputs are set as $YY^t_{r0}\lambda^t_j = [y^t_{r0}, 1.1y^t_{r0}]\lambda^t_j$.

3.2.4. Efficiency Decomposition Models

To study technological levels and environmental emission capacities, it is necessary to calculate PE and EE. PE focuses on input utilization and desirable outputs, while it does not consider desirable outputs, such as carbon dioxide and waste gas. EE only considers environmental impacts, measuring inputs and undesired outputs. PE and EE can be defined as follows:

$$PE = 1 - \left(\sum_{i_1^F=1}^{I_1^F} B^t_{i_1^F 0} d^t_{i_1^F 0} + \sum_{i_2^F=1}^{I_2^F} B^t_{i_2^F 0} d^t_{i_2^F 0} + \sum_{i_1^S=1}^{I_1^S} B^t_{i_1^S 0} d^t_{i_1^S 0} + \sum_{i_2^S=1}^{I_2^S} B^t_{i_2^S 0} d^t_{i_2^S 0} + \sum_{r_1^S=1}^{R_1^S} B^t_{r_1^S 0} d^t_{r_1^S 0} \right) \quad (6)$$

$$EE = 1 - \left(\sum_{i_1^F=1}^{I_1^F} B^t_{i_1^F 0} d^t_{i_1^F 0} + \sum_{i_2^F=1}^{I_2^F} B^t_{i_2^F 0} d^t_{i_2^F 0} + \sum_{i_1^S=1}^{I_1^S} B^t_{i_1^S 0} d^t_{i_1^S 0} + \sum_{i_2^S=1}^{I_2^S} B^t_{i_2^S 0} d^t_{i_2^S 0} + \sum_{r_2^F=1}^{R_2^F} B^t_{r_2^F 0} d^t_{r_2^F 0} + \sum_{r_2^S=1}^{R_2^S} B^t_{r_2^S 0} d^t_{r_2^S 0} \right) \quad (7)$$

3.2.5. A Two-Stage BAM-G Model

Medical waste recycling systems are complex, encompassing various stages, such as segregation and collection, preliminary harmless treatment, storage, transportation, harmless disposal of waste, landfill, and recovery of available resources. It is important to note that the "black box" DEA method does not account for the internal network structure of systems, and, as a result, it cannot accurately reflect the internal efficiency of these systems [31]. To address this limitation, we consider the classification, collection, and transportation of medical waste as the first stage, referred to as the MWCS, and the disposal of medical waste as the second stage, known as the MWTS. By examining the intermediate outputs between the two stages, we can "open the black box" to identify the specific segments that affect the efficiency of the medical waste recycling system [32]. The MWCS efficiency of DMU_j can be evaluated by model (8).

$$\begin{aligned}
& Max \sum_{i_1^F=1}^{I_1^F} B^t_{i_1^F 0} d^t_{i_1^F 0} + \sum_{i_2^F=1}^{I_2^F} B^t_{i_2^F 0} d^t_{i_2^F 0} + \sum_{r_1^F=1}^{R_1^F} B^t_{r_1^F 0} d^t_{r_1^F 0} + \sum_{r_2^F=1}^{R_2^F} B^t_{r_2^F 0} d^t_{r_2^F 0} \\
& \sum_{j=1}^{J} x^t_{i_1^F} \lambda^t_j - d^t_{i_1^F 0} = x^t_{i_1^F 0} \\
& \sum_{j=1}^{J} x^t_{i_2^F} \lambda^t_j + d^t_{i_2^F 0} = x^t_{i_2^F 0} \\
& \sum_{j=1}^{J} z^t_{r_1^F} \lambda^t_j - d^t_{r_1^F 0} = z^t_{r_1^F 0} \\
& \sum_{j=1}^{J} y^t_{r_2^F} \lambda^t_j + d^t_{r_2^F 0} = y^t_{r_2^F 0} \\
& \sum_{j=1}^{J} x^t_{i_1^F} \lambda^t_j \le \overline{x}_{i_1^F} \\
& \sum_{j=1}^{J} x^t_{i_2^F} \lambda^t_j \ge \underline{x}_{i_2^F} \\
& \sum_{j=1}^{J} z^t_{r_1^F} \lambda^t_j \ge \overline{z}_{r_1^F} \\
& \sum_{j=1}^{J} y^t_{r_2^F} \lambda^t_j \ge \underline{y}_{r_2^F} \\
& \sum_{t=1}^{T} \sum_{j=1}^{J} \lambda^t_j = 1 \\
& \lambda^t_j \ge 0, d^t_{i_1^F} \ge 0, d^t_{i_2^F} \ge 0, d^t_{r_1^F} \ge 0, d^t_{r_2^F} \ge 0 \\
& j = 1, \ldots\ldots, J; i_1^F = 1, \ldots\ldots, I_1^F; i_2^F = 1, \ldots\ldots, I_2^F; r_1^F = 1, \ldots\ldots, R_1^F; \\
& r_2^F = 1, \ldots\ldots, R_2^F; t = 1, \ldots\ldots T
\end{aligned} \quad (8)$$

In the MWTS, annual precipitation needs to be invested again. MWTS efficiency can be evaluated by model (9).

$$
\begin{aligned}
&Max \sum_{r_1^F=1}^{R_1^F} B^t_{r_1^F 0} d^t_{r_1^F 0} + \sum_{i_1^S=1}^{I_1^S} B^t_{i_1^S 0} d^t_{i_1^S 0} + \sum_{i_2^S=1}^{I_2^S} B^t_{i_2^S 0} d^t_{i_2^S 0} + \sum_{r_1^S=1}^{R_1^S} B^t_{r_1^S 0} d^t_{r_1^S 0} \\
&+ \sum_{r_2^S=1}^{R_2^S} B^t_{r_2^S 0} d^t_{r_2^S 0} \\
&\sum_{j=1}^{J} z^t_{r_1^F} \lambda^t_j - d^t_{r_1^F 0} = z^t_{r_1^F 0} \\
&\sum_{j=1}^{J} x^t_{i_1^S} \lambda^t_j + d^t_{i_1^S 0} = x^t_{i_1^S 0} \\
&\sum_{j=1}^{J} x^t_{i_2^S} \lambda^t_j + d^t_{i_2^S 0} = x^t_{i_2^S 0} \\
&\sum_{j=1}^{J} y^t_{r_1^S} \lambda^t_j - d^t_{r_1^S 0} = y^t_{r_1^S 0} \\
&\sum_{j=1}^{J} y^t_{r_2^S} \lambda^t_j + d^t_{r_2^S 0} = y^t_{r_2^S 0} \\
&\sum_{j=1}^{J} z^t_{r_1^F} \lambda^t_j \le \overline{z}_{r_1^F} \\
&\sum_{j=1}^{J} x^t_{i_1^S} \lambda^t_j \le \overline{x}_{i_1^S} \\
&\sum_{j=1}^{J} x^t_{i_2^S} \lambda^t_j \ge \underline{x}_{i_2^S} \\
&\sum_{j=1}^{J} y^t_{r_1^S} \lambda^t_j \ge \overline{y}_{r_1^S} \\
&\sum_{j=1}^{J} y^t_{r_2^S} \lambda^t_j \ge \underline{y}_{r_2^S} \\
&\sum_{t=1}^{T} \sum_{j=1}^{J} \lambda^t_j = 1 \\
&\lambda^t_j \ge 0, d^t_{r_1^F} \ge 0, d^t_{i_1^S} \ge 0, d^t_{i_2^S} \ge 0, d^t_{r_1^S} \ge 0, d^t_{r_2^S} \ge 0 \\
&j = 1, \ldots\ldots, J; r_1^F = 1, \ldots\ldots, R_1^F; i_1^S = 1, \ldots\ldots, I_1^S; i_2^S = 1, \ldots\ldots, I_2^S; \\
&r_1^S = 1, \ldots\ldots, R_1^S; r_2^S = 1, \ldots\ldots, R_2^S; t = 1, \ldots\ldots T
\end{aligned}
\tag{9}
$$

$$
B^t_{r_1^F 0} = \frac{1}{\left(I_1^F + I_2^F + I_1^S + I_2^S + R_2^F + R_1^S + R_2^S\right)\left(\overline{z}_{r_1^F} - z^t_{r_1^F 0}\right)}, \overline{z}_{r_1^F} = \max\left\{ z^t_{r_1^F}, r_1^F = 1, \ldots, R_1^F; t = 1, 2, \ldots, T \right\} \tag{10}
$$

4. Empirical Study

4.1. Variables and Data

China's new first-tier cities, as identified by First Financial News since 2013, are assessed based on five major indicators: commercial resource aggregation, urban hub, human activity, lifestyle diversity, and future potential. This evaluation involves data from 170 well-known enterprises, user behavior data from 19 internet companies, and data institutions, covering 337 prefecture-level and above cities in China [33]. The efficiency of medical waste recycling systems in these cities can be seen as a microcosm of the urbanization process in China, which is crucial for understanding the level of China's medical waste recycling systems.

DEA is designed to determine the relative efficiency of each *DMU* compared to other *DMUs* and to classify them as either efficient (on the boundary of the production possibility set) or inefficient (within the boundary). Smaller data discrepancies among

DMUs can provide a more precise efficiency assessment. If the data discrepancies are large, this can lead to increased volatility in the assessment results, and outliers may have a disproportionate impact on the determination of the efficiency frontier, thereby distorting the efficiency scores. The differences in socio-economic factors and demographic variables among China's new first-tier cities are relatively small [34]. Selecting these cities as the *DMUs* can help to minimize the differences and ensure the accuracy of the efficiency results. To the best of our knowledge, there are no existing studies that have evaluated the efficiency of medical waste recycling systems, nor has there been any research that has assessed the efficiency of medical waste recycling systems in China's new first-tier cities.

This paper selects 15 cities in the list of New First-Tier Cities since 2022, which includes Chengdu, Chongqing, Hangzhou, Xi'an, Wuhan, Suzhou, Zhengzhou, Nanjing, Tianjin, Changsha, Dongguan, Ningbo, Foshan, Hefei, and Qingdao, as the *DMUs*. By employing a two-stage BAM-G model to calculate the efficiency of the medical waste recycling systems, the study aims to explore which subsystems are more sensitive to the medical waste recycling systems in these cities, thereby providing feasible recommendations for local improvements.

As shown in Figure 5, the medical waste generated volume in these cities showed an upward trend from 2017 to 2019, slowed down from 2019 to 2021, and then increased in 2022. This phenomenon is mainly attributed to the outbreak of COVID-19 in 2019 and the surge in medical activities caused by the shift in China's epidemic prevention policies from "preventing infection" to "protecting health and preventing severe cases" in 2022. Figure 6 displays a heat map of the medical waste volumes generated in these cities from 2017 to 2022.

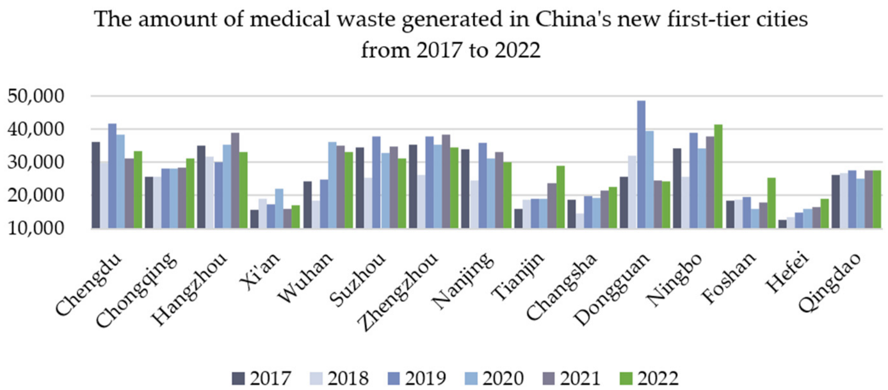

Figure 5. Medical waste generated volumes.

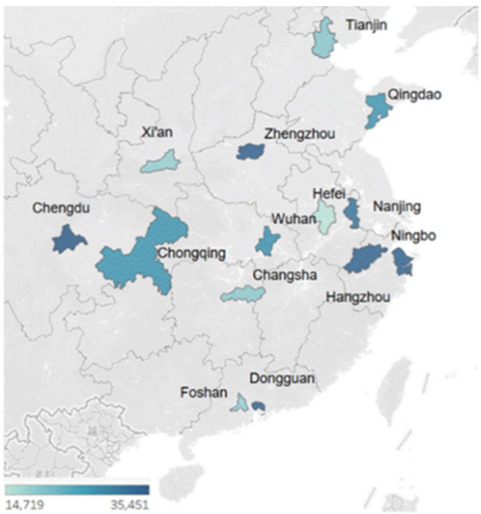

Figure 6. Heat map of medical waste generated volumes from 2017 to 2022.

Table 3 summarizes the descriptive statistics of the inputs and outputs of medical waste recycling systems. The variables of inputs and outputs are defined as follows. Due to the lack of direct data sources for some indicators, we estimated the relevant indicators based on previous research studies [35–37], and the specific estimation method was as follows.

Medical waste generated volume. Domestically and internationally, the medical waste generated volume was primarily estimated based on a certain medical waste production coefficient. Referring to the forecasting method proposed by Li [35], this paper derived the following formula for the medical waste generated volume.

Medical waste generated volume = Outpatient medical waste generated volume × inpatient medical waste generated volume

Outpatient medical waste generated volume = The number of medical treatments provided by health and medical institutions × Medical waste generation per patient visit

Inpatient medical waste generated volume = The actual number of hospital beds in the city × Bed occupancy rate × Medical waste generation per bed

For cities that did not disclose the number of medical beds, the inpatient medical waste generated volume was estimated using the total annual number of hospital admissions and the average length of hospital stays per year. The formula used for this estimation is as follows:

Inpatient medical waste generated volume = Total annual number of hospital admissions × The average length of hospital stays per year × Medical waste generation per bed

Referring to the assessment by the United Nations Planning Agency on waste generation rates from various parts of the world [38], it is indicated that hospitals produce approximately 0.5 to 1 kg of waste per bed per day. Therefore, the medical waste generation per bed is arbitrarily taken to be between 0.5 and 1 kg. For outpatient departments, the daily waste generation is about 1 kg for every 20 to 30 people. Hence, the medical waste generation per patient visit is arbitrarily taken to be between 0.03 and 0.05 kg.

Annual precipitation. The data on annual precipitation was obtained from the China Statistical Yearbook on the Environment.

Labor. Manual skilled personnel are responsible for skilled operations and maintenance, logistical support, and services. Therefore, this paper selected manual skilled personnel as the labor input for the MWCS.

Transportation cost. In this paper, we estimated the transportation costs using the following formula.

Transportation cost = The price of gasoline × City's fuel consumption × Medical waste collected volume accounts for the proportion of road transportation

Degree of government support. There are currently no direct data available regarding specific investments by the municipal government in MWTS disposal projects. However, there are concrete data regarding the completion of investment in provincial solid waste management projects. The amount of investment by the government in solid waste management also reflects the government's level of attention to the disposal of medical waste. Therefore, this article selected the completed investment in provincial solid waste management projects as a representative of the government's level of support.

Energy. The data on energy were obtained from the China Electric Power Yearbook.

Operating costs. Medical waste is primarily disposed of through disinfection and high-temperature incineration, with operational costs ranging from 0.15 to 0.23 ten thousand CNY per ton [39]. Therefore, this paper calculated the operational costs by multiplying the medical waste disposal volume by a randomly generated factor between 0.15 and 0.23.

Medical waste collected volume. The Municipal Bureau of Ecology and Environment issues annual announcements regarding information on the prevention and control of solid waste pollution.

Medical waste disposal volume. According to the survey, the centralized disposal rate for medical waste in China currently stands at 100%. Hence, the medical waste disposal volume is equivalent to the medical waste collected volume.

Table 3. Statistical description of input and output indicators from 2017 to 2022.

Indicators		Unit	Max	Min	Mean	Std. Dev.
Medical waste collection, transportation subsystem (MWCS)	Medical waste generated volume	10 thousand tons	6.334	0.848	2.846	1.201
	Annual precipitation	mm	2062.700	459.200	1225.650	445.963
	Labor	10 thousand people	9.380	0.810	4.893	2.282
	Transportation cost	10 thousand tons	833.154	16.528	151.953	162.680
	Medical waste collected volume *	10 thousand tons	3.590	0.633	1.813	0.710
	CO_2 emissions	10 thousand tons	0.313	0.007	0.064	0.067
Medical waste treatment subsystem (MWTS)	Degree of government support	10 thousand CNY	13,167.900	0.000	1353.944	2682.078
	Annual precipitation	mm	2062.70	459.20	1224.91	458
	Energy	Million kwh	7.973	0.806	4.034	2.249
	Operating costs	10 thousand CNY	1775.637	341.785	724.672	318.658
	Medical waste collected volume *	10 thousand tons	5.900	0.633	2.084	1.247
	Medical waste disposal volume	10 thousand tons	5.900	0.633	1.917	0.949
	Waste gas	10 thousand tons	0.536	0.022	0.186	0.110

Note: * indicates intermediate variable.

CO_2 emissions. Medical waste is transported via road; hence, this paper estimated the CO_2 emissions generated by the transportation of medical waste by considering indicators such as the proportion of the medical waste collected volume to the total road freight volume and the CO_2 emissions produced by road transportation. The specific formula is as follows.

CO_2 emissions = The proportion of medical waste collected volume to the total road freight volume $\times$ CO_2 emissions produced by road transportation

Waste gas and residue. This paper estimated the waste gas and residue by considering the proportion of the medical waste disposal volume to the total volume of municipal solid waste.

Waste gas and residue = The proportion of medical waste disposal volume to the total volume of municipal solid waste $\times$ The total amount of urban waste gas and residue

The data used in the study cover the period from 2017 to 2022. They were collected from various sources: the Health Commission; Annual Statistics on the Environment in China; the China Electric Power Yearbook; the China Statistical Yearbook; the China Energy Statistical Yearbook; the maximum retail prices of gasoline and diesel in provinces; municipalities and central cities; Local Statistical Bureaus; the Municipal Bureau of Ecology and Environment; and the China CO_2 Accounting Database. Table 4 reports the detailed data sources.

Table 4. Sources of statistics.

Index	Source
Medical waste generated volume	Health Commission
Annual precipitation	Annual Statistics on the Environment in China
Labor	Health Commission
Transportation cost	China Statistical Yearbook, China Energy Statistical Yearbook, maximum retail prices of gasoline and diesel in provinces, municipalities and central cities
Degree of government support	Local Statistical Bureaus
Energy	China Electric Power Yearbook
Operating costs	China Energy Statistical Yearbook
Medical waste collected volume	Municipal Bureau of Ecology and Environment
Medical waste disposal volume	Municipal Bureau of Ecology and Environment
CO_2 emissions	Annual Statistics on the Environment in China, China CO_2 Accounting Database
Waste gas and residue	Annual Statistics on the Environment in China

4.2. Empirical Results

This section begins by employing the BAM-G and BAM-VF-G models to evaluate China's new first-tier cities' medical waste recycling systems' efficiency between 2017 and 2022. Subsequently, PE and EE are calculated to analyze the technological level and environmental emission capacity. Finally, the efficiencies of MWCSs and MWTSs are calculated to examine the internal factors influencing systems efficiency.

4.2.1. The Efficiency of BAM-G and BAM-VF-G

We use the BAM-G model to estimate the efficiency of these cities' medical waste recycling systems. Table 5 summarizes the system efficiency scores from 2017 to 2022. It can be observed that Hangzhou has been the least efficient city in terms of medical waste recycling, with an average efficiency score of a mere 0.432 between the years 2017 and 2022. Suzhou, Zhengzhou, Nanjing, Tianjin, Dongguan, Foshan, Hefei, and Qingdao all have efficiency scores of 1, indicating that the medical waste recycling systems established in these cities are relatively rational and that they have taken a leading position in medical waste recycling compared to other cities, such as Chengdu, Chongqing, and Hangzhou. These inefficient cities can learn from the successful experiences of cities like Suzhou and Zhengzhou to identify directions for improvement and enhancement. However, unfortunately, this analysis does not identify the differences among these eight efficient cities. To further rank Suzhou, Zhengzhou, Nanjing, Tianjin, Dongguan, Foshan, Hefei, and Qingdao specifically, the BAM-VF-G model was employed for efficiency measurement.

Table 5. The efficiencies of medical waste recycling systems in selected cities from 2017 to 2022 obtained from the BAM-G model.

CNFCs	2017	2018	2019	2020	2021	2022	Mean
Chengdu	0.751	1.000	1.000	0.658	1.000	1.000	0.901
Chongqing	1.000	1.000	0.541	0.660	0.740	0.339	0.713
Hangzhou	0.581	0.449	0.535	0.369	0.275	0.381	0.432
Xi'an	1.000	1.000	0.693	1.000	1.000	1.000	0.949
Wuhan	0.575	1.000	1.000	0.460	1.000	1.000	0.839
Suzhou	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Zhengzhou	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Nanjing	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Tianjin	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Changsha	0.719	1.000	1.000	0.444	1.000	0.642	0.801
Dongguan	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Ningbo	1.000	0.675	1.000	0.501	0.296	0.461	0.655
Foshan	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Hefei	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Qingdao	1.000	1.000	1.000	1.000	1.000	1.000	1.000

The principle of the virtual frontier is to set the input intervals for the *DMUs* as [0.9, 1] and the output intervals as [1, 1.1], thereby generating a new set of reference *DMUs* through random production. Since the efficiency of the reference *DMUs* produced randomly is higher than that of the evaluated set of *DMUs*, it is easier to differentiate between the efficiencies of effective *DMUs*. The efficiency scores obtained through the virtual frontier will also be lower than those derived from the BAM-G model. The results are shown in Table 6. It can be observed that none of the *DMUs* has an efficiency score of 1, and all are lower than the efficiency scores obtained from the BAM-G model. A comparison of the efficiency scores and rankings calculated by the BAM-G model and the BAM-VF-G model is presented in Table 7. The *DMUs* with efficiency scores of 1, as calculated by the BAM-G model, are ranked in the following order: Foshan, Tianjin, Qingdao, Dongguan, Hefei, Suzhou, Zhengzhou, and Nanjing.

Table 6. The efficiencies of medical waste recycling systems in selected cities from 2017 to 2022 obtained from the BAM-VF-G model.

CNFCs	2017	2018	2019	2020	2021	2022	Mean
Chengdu	0.032	0.035	0.033	0.035	0.025	0.027	0.031
Chongqing	0.029	0.020	0.021	0.019	0.213	0.103	0.067
Hangzhou	0.015	0.016	0.017	0.017	0.061	0.023	0.025
Xi'an	0.036	0.105	0.045	0.101	0.114	0.018	0.070
Wuhan	0.016	0.020	0.019	0.019	0.114	0.115	0.050
Suzhou	0.094	0.096	0.097	0.093	0.027	0.103	0.085
Zhengzhou	0.044	0.033	0.028	0.045	0.112	0.111	0.062
Nanjing	0.054	0.038	0.044	0.026	0.024	0.027	0.036
Tianjin	0.199	0.101	0.110	0.108	0.329	0.324	0.195
Changsha	0.026	0.051	0.024	0.027	0.118	0.223	0.078
Dongguan	0.106	0.104	0.099	0.102	0.110	0.220	0.124
Ningbo	0.018	0.021	0.019	0.016	0.100	0.024	0.033
Foshan	0.441	0.436	0.440	0.437	0.052	0.110	0.319
Hefei	0.118	0.100	0.095	0.113	0.113	0.112	0.109
Qingdao	0.113	0.111	0.222	0.107	0.111	0.114	0.130

Table 7. The efficiencies of medical waste recycling systems in selected cities obtained from the BAM-G model and the BAM-VF-G model.

CNFCs	BAM-G	Rank (BAM-G)	BAM-VF-G	Rank (BAM-VF-G)
Chengdu	0.901	10	0.031	14
Chongqing	0.713	13	0.067	9
Hangzhou	0.432	15	0.025	15
Xi'an	0.949	9	0.070	8
Wuhan	0.839	11	0.050	11
Suzhou	1.000	1	0.085	6
Zhengzhou	1.000	1	0.062	10
Nanjing	1.000	1	0.036	12
Tianjin	1.000	1	0.180	2
Changsha	0.801	12	0.078	7
Dongguan	1.000	1	0.124	4
Ningbo	0.655	14	0.033	13
Foshan	1.000	1	0.386	1
Hefei	1.000	1	0.109	5
Qingdao	1.000	1	0.130	3

These fifteen cities are categorized into two groups: efficient *DMUs* and inefficient *DMUs*, as depicted in Figure 7. Among them, Foshan, Tianjin, and Qingdao are the three cities with efficient scores, while Hangzhou, Chengdu, and Ningbo are the three cities with inefficient scores. Analyzing the efficiency scores of these two groups of cities from 2017 to 2022, it can be observed that during the years 2017 to 2019, there was an upward trend in the efficiency scores for both groups of cities. However, in the years 2020 to 2021, there was a decline in the efficiency scores of all cities to varying degrees. What is distinct is that in the year 2022, the efficiency scores for the group of efficient cities increased, while the efficiency scores for the group of inefficient cities decreased.

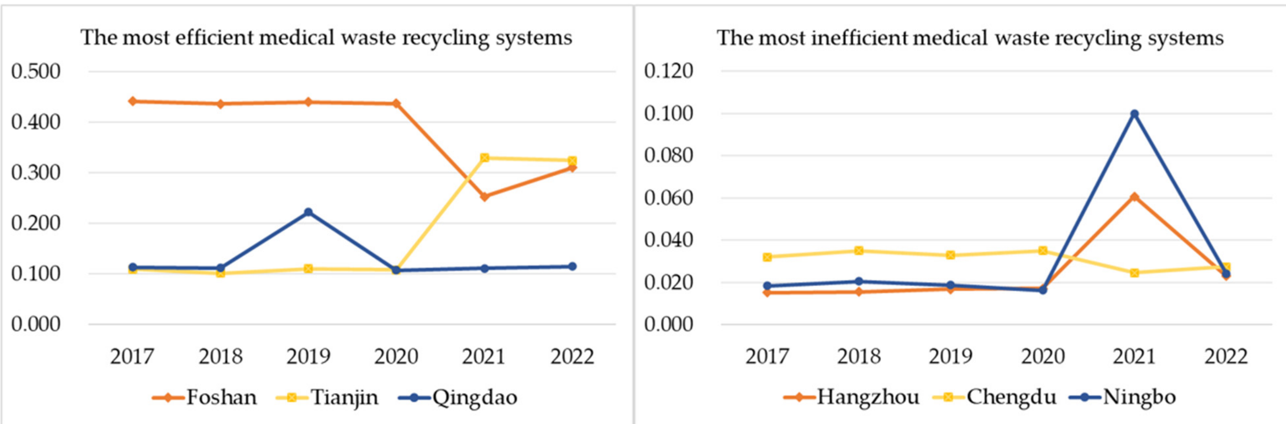

Figure 7. Trends in efficiency in the top three and bottom three cities.

The COVID-19 pandemic has had a profound impact on China, the year 2020 being marked as the most challenging in terms of the speed of transmission, the extent of contagion, and the difficulty of prevention and control since the founding of the People's Republic of China. The pandemic has led to a surge in medical activities, resulting in a continuous increase in the medical waste generated volume. In 2020, a total of 1.26 million tons of medical waste was produced nationwide, a year-on-year increase of 6.8%. In 2021, the total amount of medical waste generated nationwide reached 1.4 million tons (including 201,000 tons of epidemic-related medical waste), representing an increase of 18.6% and 11.1%, respectively, compared to the years 2019 and 2020. The disposal of medical waste in China mainly relies on the incineration capacity of domestic waste incineration enterprises.

As the amount of domestic waste increases annually, the disposal capacity for medical waste is increasingly being squeezed. The sharp increase in the medical waste generated volume during the pandemic has put immense pressure on the already limited capacity for the recycling and disposal of medical waste, significantly reducing the efficiency of the recycling system. The outbreak has exposed the shortcomings of the medical waste recycling system.

On 26 February 2020, ten departments, including the National Health Commission, the Ministry of Ecology and Environment, and the Ministry of Housing and Urban–Rural Development, issued the "Comprehensive Management Work Plan for Medical Waste from Medical Institutions". The plan provides specific guidelines for strengthening the comprehensive management of medical waste from medical institutions to achieve reduction, resource utilization, and harmless treatment of waste. On 25 March 2020, cities such as Foshan and Heyuan were urged to accelerate the construction of new medical waste facilities and to put them into operation as soon as possible. On 26 March, Shandong Province passed the first provincial-level local regulation on medical waste management, establishing a comprehensive system for the collection, transportation, and disposal of medical waste. The regulation also calls for increased financial investment and the consideration of geographical location and population served in setting up regional facilities for the collection, storage, and disposal of medical waste.

With the reclassification of COVID-19 from a "Class B infectious disease managed as Class A" to "Class B managed as Class B", there was a resurgence in medical activities, leading to a peak in the medical waste generated volume. Cities including Foshan, Tianjin, and Qingdao were able to mitigate the impact on their medical waste recycling systems due to the bolstering of their previously identified shortcomings in recycling capabilities. The enhancements made to these systems allowed them to maintain their operational efficiency despite the increased demand. In contrast, cities like Hangzhou, Chengdu, and Ningbo did not take the necessary steps to improve the efficiency of their medical waste recycling systems prior to the rise in medical activities in 2022. This lack of preparation left their recycling systems vulnerable and ill-equipped to handle the surge, leading to a significant setback in their performance throughout the year. This is also one of the reasons why these cities' medical waste recycling systems are considered inefficient.

According to the classification standards of the National Bureau of Statistics, China is divided into four major regions: the eastern, central, western, and northeastern regions. Since the new first-tier cities evaluated in this paper do not include those from the northeastern region, Table 8 categorizes the efficiency of the medical waste recycling systems of the new first-tier cities in the eastern, central, and western regions. It can be observed that the majority of new first-tier cities are concentrated in the eastern region, and the cities with efficient scores are all located in the eastern region. The efficiencies of the central and western regions are comparable, indicating that the development level of China's medical waste recycling systems is not balanced and that there is still significant room for development in the central and western regions.

Table 8. Regional distribution of efficiency grades of medical waste recycling systems.

Grade	Eastern	Central	Western
Efficient	Foshan, Tianjin, Qingdao, Dongguan, Hefei		
Mid-efficient	Suzhou,	Changsha, Zhengzhou	Xi'an, Chongqing
Inefficient	Nanjing, Ningbo, Hangzhou	Wuhan	Chengdu

4.2.2. Production Efficiency and Environment Efficiency Obtained from BAM-G

The average PE and EE scores are shown in Figure 8. Zhengzhou, Qingdao, Dongguan, Nanjing, Suzhou, Foshan, and Tianjin all have PE and EE scores of 1, indicating a high technological level and environmental emission capacity. It is worth noting that Hangzhou still maintains low PE and EE scores, with the lowest scores at 0.334 and 0.281, respectively. PE and EE in these cities are closely correlated. This phenomenon can be attributed to two factors. First, cities with higher levels of waste disposal technology have stricter environmental requirements for waste management, leading to a strong correlation between production and environmental emission capacity. Second, environmentally friendly companies have a higher appeal to customers, contributing to the close relationship between production and environmental emission capacity.

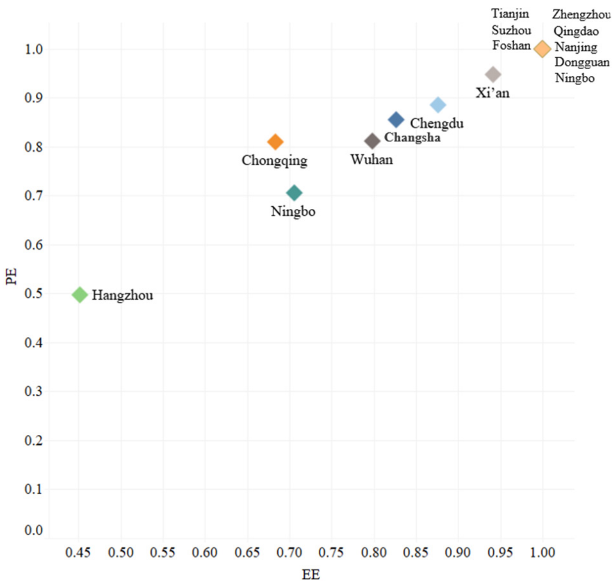

Figure 8. Average PE and EE of selected cities from 2019 to 2022.

As shown in Figure 9, the new first-tier cities' medical waste recycling systems had inefficient scores (the highest is only 0.942) over the entire sample period. Unified efficiency, PE, and EE show an increasing trend from 2017 to 2018, followed by a slight decline in 2019. They reach their lowest point in 2020 and gradually recover in 2021. When medical activities surged again in 2022, overall efficiency, PE, and EE decreased once more, revealing a significant deficiency and severe lack of resilience in the medical waste recycling systems of these cities. In particular, EE was the most severely affected, suggesting the need for additional attention to environmental protection in medical waste recycling systems.

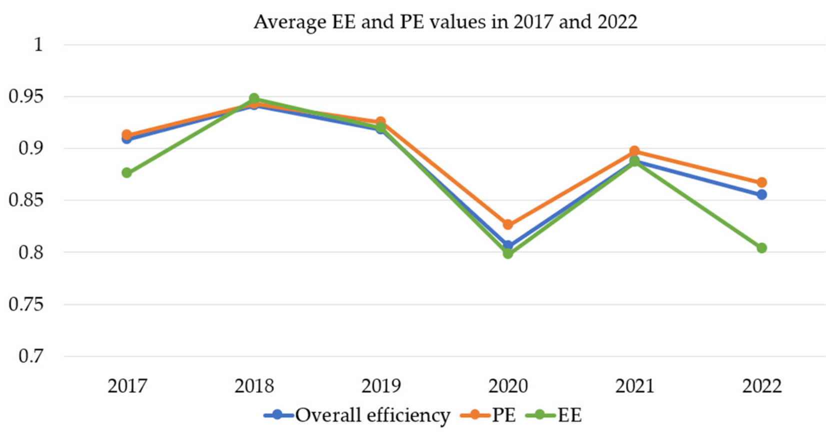

Figure 9. Comparisons of unified efficiency, PE, and EE from 2017 to 2022.

Incineration disposal technology can achieve the objectives of harmlessness, reduction, stabilization, and complete destruction of medical waste, demonstrating good applicability to various types of waste, which is why it has been widely applied. However, the process of disposing of medical waste can produce substances such as dioxins and heavy metals, especially when the input of waste is unstable, leading to numerous issues in tail gas purification and significant environmental risks. Particularly during the pandemic period, the sudden surge in the generation of medical waste increased the difficulty of disposal, making it challenging to ensure the quality of tail gas treatment. The improvement in EE is closely related to the technology used for the disposal of medical waste. Limited by disposal technology, using a combination of various treatment methods (such as incineration and high-temperature treatment technologies) can enhance environmental efficiency. Different types of waste require the integration of different disposal technologies. However, the unfortunate reality on a global scale is that a large amount of healthcare waste is not disposed of using the correct technology. The enhancement of EE undoubtedly requires the investment of more human, material, and financial resources, which can impact production efficiency. Balancing EE with cost will be a topic that urgently needs to be discussed.

4.2.3. The MWCS Efficiency and the MWTS Efficiency Obtained from a Two-Stage BAM-G

Table 9 illustrates the efficiency of MWCSs and MWTSs in CNFCs from 2017 to 2022. Suzhou, Tianjin, Dongguan, Foshan, and Qingdao have higher efficiency in MWCSs and the MWTSs, indicating that these five cities have certain reference values for other cities in medical waste recycling. However, Hangzhou has the lowest MWCS and MWTS efficiencies for the past five years, at 0.493 and 0.440, respectively.

As shown in Figure 10, the efficiencies of MWCSs show a gradual increase from 2017 to 2018, with 10 cities achieving a score of 1 in 2018. The efficiencies of MWTSs continue to increase from 2017 to 2019, with 12 cities achieving a score of 1 in 2019. Both the MWCSs and the MWTSs experienced their lowest efficiencies in 2020, with a gradual recovery observed in 2021. It is important to highlight that even though the overall efficiency and the efficiencies of MWTSs experienced a decline in 2022, there has been an observed improvement in MWCSs. This indicates that the resilience of the MWCSs has been significantly improved since the year 2020.

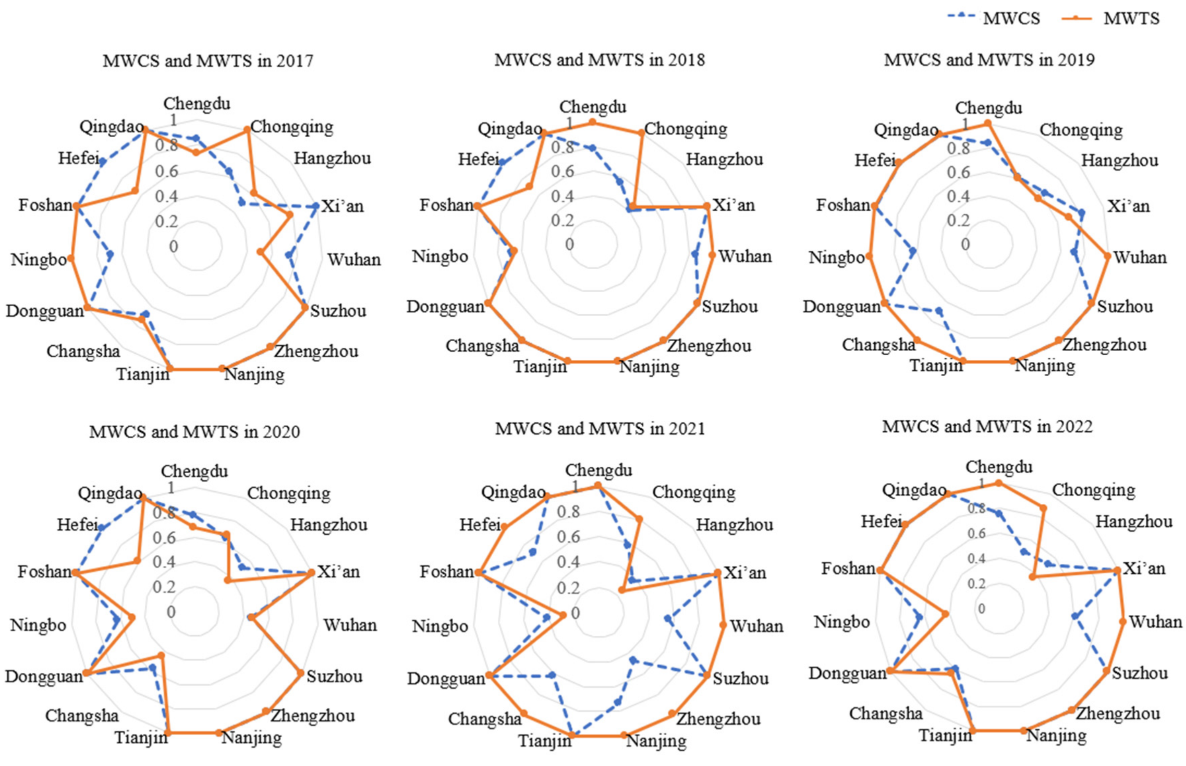

Figure 10. Comparisons of the efficiencies of MWCSs and MWTSs from 2017 to 2022.

Table 9. The efficiencies of medical waste collection, transportation subsystems (MWCSs), and medical waste treatment subsystems (MWTSs) in selected cities.

CNFCs	**MWCS**								**MWTS**							
	2017	**2018**	**2019**	**2020**	**2021**	**2022**	**Mean**	**Rank**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**Mean**	**Rank**
Chengdu	0.849	0.789	0.836	0.772	0.772	0.761	0.834	10	0.735	1.000	1.000	0.674	1.000	1.000	0.901	10
Chongqing	0.640	0.556	0.607	0.643	0.643	0.498	0.586	14	1.000	1.000	0.595	0.670	0.801	0.878	0.824	11
Hangzhou	0.496	0.414	0.633	0.523	0.523	0.529	0.493	15	0.618	0.453	0.564	0.372	0.260	0.374	0.440	15
Xi’an	1.000	1.000	0.821	1.000	1.000	1.000	0.970	6	0.789	1.000	0.710	1.000	1.000	1.000	0.916	9
Wuhan	0.745	0.859	0.721	0.465	0.465	0.613	0.659	12	0.512	1.000	1.000	0.474	1.000	1.000	0.831	12
Suzhou	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
Zhengzhou	1.000	1.000	1.000	1.000	1.000	1.000	0.913	9	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
Nanjing	1.000	1.000	1.000	1.000	1.000	1.000	0.956	7	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
Tianjin	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
Changsha	0.680	1.000	0.692	0.563	0.563	0.592	0.691	11	0.731	1.000	1.000	0.438	1.000	0.640	0.802	5
Dongguan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
Ningbo	0.688	0.675	0.634	0.620	0.620	0.640	0.611	13	1.000	0.652	1.000	0.497	0.281	0.427	0.643	14
Foshan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
Hefei	1.000	1.000	1.000	1.000	1.000	1.000	0.950	8	0.647	0.696	1.000	0.606	1.000	1.000	0.825	13
Qingdao	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1

Figure 11 illustrates a strong correlation between the overall efficiency and the efficiency of MWCSs and MWTSs. The efficiency evaluation of MWCSs stands at 0.844, which is 0.035 lower than that of MWTSs. The inefficiency of MWCSs exposes the existing challenges in China's medical waste segregation, collection, preliminary harmless treatment, storage, and transportation processes.

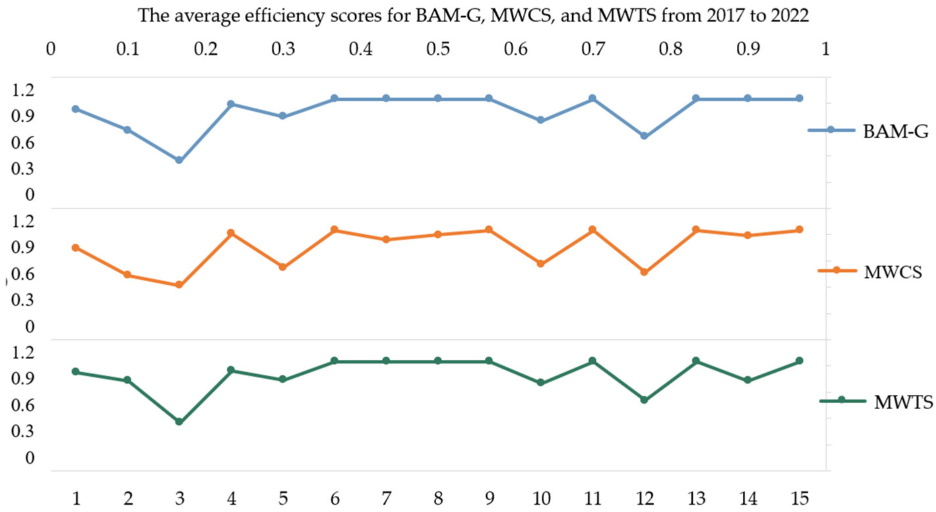

Figure 11. The average efficiency scores for BAM-G, MWCSs, and MWTSs from 2017 to 2022.

4.3. Discussion

Through the above analysis, our main findings are summarized as follows:

1. According to the results obtained from the BAM-VF-G model, Foshan is the most efficient in terms of medical waste recycling and stayed ahead of Qingdao. Similar to when the BAM-G model was used, Hangzhou, Ningbo, and Chengdu were again found to be the most inefficient provinces. Suzhou, Tianjin, Dongguan, Foshan, and Qingdao have efficiencies of 1 in PE, EE, and both substages. This is closely linked to the government's policy support, the application of relevant advanced technologies, and the improvement in personnel quality.
2. EE remains a significant factor contributing to the inefficiency of the medical waste recycling systems and it lacks resilience significantly. Figure 9 indicates that EE has consistently been lower than the overall efficiency and PE. With the advancement of science and technology, the medical waste generated volume can now be fully managed by existing medical waste disposal centers. However, addressing the pollution from exhaust gases and waste residues produced during the disposal process remains a formidable challenge. Therefore, the government should intensify its research and development investment in medical waste disposal to reduce the environmental pollution caused by medical waste in MWTSs.
3. The COVID-19 pandemic led to a surge in the generation of medical waste, posing challenges to the collection and disposal of medical waste and resulting in a decline in the efficiency of medical waste recycling. In the new first-tier cities, the unified efficiency of medical waste recycling decreased by 2.52% in 2019 and further declined by 12.18% in 2020. There was a brief recovery in 2021, but after the adjustment of epidemic prevention policies in 2022, the medical waste generated saw another peak, and the overall efficiency decreased by 3.67%. To enhance the efficiency of the medical waste recycling system and strengthen its resilience, it is important to adhere to and implement the "Green Development of China in the New Era", strengthen environmental protection, and resolutely fight the critical battle against pollution; the government and relevant entities must continue to focus on medical waste recycling.

4. MWCSs have consistently been the primary bottleneck in the efficiency of the medical waste recycling system. On one hand, the medical waste collection process is not standardized, and there is a lack of professional recycling personnel. On the other hand, the medical waste recycling system network is irrational, leading to high transportation costs and posing challenges to transportation safety. Especially after the outbreak of the COVID-19 pandemic, with the surge in the generation of medical waste, medical waste recycling efficiency has significantly declined, highlighting the poor resilience of the MWCSs.

5. Conclusions and Policy Recommendations

5.1. Conclusions and Limitations

Resource utilization and environmental governance have become hot topics of current research. Waste recycling is a key measure in the current situation, receiving widespread attention and calls from all sectors of society. As a special waste, scientific recycling and proper treatment of medical waste can avoid secondary pollution and promote resource reuse. The medical waste recycling system encompasses two stages: MWCSs and MWTSs. Unlike other inputs, where the expectation is to achieve the maximum output with the minimum input, the medical waste collected volume, precipitation levels, and the degree of government support are considered input indicators (harmful inputs or naturally occurring conditions that are non-cost inputs), and it is desired to have as much of these inputs as possible, hence they are referred to as undesirable inputs. To evaluate the efficiency of the medical waste recycling systems, this paper proposes a two-stage G-BAM model that considers both non-desired inputs and outputs. To address the situation where multiple *DMUs* have an efficiency value of 1, we extend a virtual frontier to rank efficient *DMUs* and propose the BAM-VF-G model. Secondly, by calculating PE and EE, the production and environmental efficiencies of CNFCs are explored. Finally, the efficiency of the medical waste recycling system is decomposed into MWCSs and MWTSs to further understand the internal operations of the medical waste recycling system. The conclusions are as follows.

1. From 2017 to 2019, the efficiency of the medical waste recycling systems in new first-tier cities, as well as all subsystems, saw significant improvements. Although the overall efficiency declined in 2020 due to the impact of the COVID-19 pandemic, it gradually increased after 2021. In recent years, in accordance with the "Comprehensive Management Plan for Medical Institution Waste", local authorities have strengthened the comprehensive management of medical institution waste, achieving waste reduction, resource utilization, and harmless treatment, resulting in fruitful outcomes in the governance of medical waste and environmental protection.
2. The PE is higher than the EE. With the continuous development and application of medical waste disposal technologies, the disposal efficiency is sufficient to meet the growing demand for the medical waste generated volume. However, due to the complexity and polluting nature of medical waste of various types, it poses a risk of environmental pollution. On the other hand, existing technologies still face insurmountable challenges, and the treatment of medical waste generates a significant amount of emissions, such as smoke and gases, which may contain harmful substances, causing pollution to the environment and reducing air quality.
3. The MWCS exhibits a lower level of efficiency. On one hand, the MWCS involves multiple stages and requires collaboration and coordination with various stakeholders, including medical institutions, government departments, and waste management enterprises. Its management encompasses several aspects, including regulation, operation, and technical support. If the management system is not robust, with inadequate supervision and unclear responsibilities, this can lead to operational inefficiencies and impact the effectiveness of the MWCS. On the other hand, medical waste originates from a wide range of sources, including hospitals, clinics, and pharmacies. However, during the initial stages of waste management and recycling system construction, there may not have been sufficient consideration of the medical waste generated

volume and the characteristics of each stage, leading to an irrational layout and incomplete coverage, which affects the overall efficiency of the MWCS.

The limitations of this paper are primarily manifested in two aspects.

1. Data Limitations: The four-year period from 2019 to 2022, which encompasses China's fight against the COVID-19 pandemic, constitutes two-thirds of the data in this paper. The evaluation results are influenced by objective factors such as policies. It would be possible to continue tracking the medical waste recycling systems of these cities to explore the efficiency of medical waste recycling under normalized conditions.
2. Model Limitations: The use of the virtual frontier method, which requires the random generation of a set of reference $DMUs$, adds complexity to the model and calculations. The handling of uncertainty and the more complex mathematical form mean that the virtual frontier method requires more computational resources and time.

5.2. Policy Recommendations

Building upon the aforementioned conclusions, policy recommendations have been proposed to enhance the efficiency of medical waste recycling systems.

1. Improve the efficiency of the MWCSs. On one hand, it is essential to promote the scientific construction of the medical waste recycling network, which includes optimizing the recycling process, selecting facilities for recycling nodes, and planning routes for medical waste transportation vehicles, thereby improving the efficiency and quality of recycling. On the other hand, the government should formulate and refine relevant regulations and standards for medical waste recycling, clarifying the management requirements and division of responsibilities for medical waste recycling.
2. Reduce environmental pollution. On the one hand, the medical waste recycling network should be optimized to minimize the exhaust pollution generated during the transportation of medical waste. On the other hand, medical waste disposal enterprises should introduce new technologies to maximize the reduction in medical waste generation and the release of emissions. At the same time, the government should implement incentive mechanisms, encouraging continuous innovation and the application of relevant technologies through R&D subsidies and tax incentives, to achieve waste reuse and resource utilization.
3. The increasing generation of medical waste and the potential for various major disasters should be addressed, and enhancing the resilience of the medical waste recycling network is essential. On the one hand, it is necessary to properly classify and manage waste within medical institutions, ensuring that all medical waste is thoroughly sorted and traceable. Encouraging leading medical institutions to guide and implement integrated waste classification and management within their medical consortia is advisable. On the other hand, strengthening the construction of centralized disposal facilities is crucial, including the establishment of at least one centralized medical waste disposal facility that meets operational requirements in each city above the prefecture level and the development of a medical waste collection, transportation, and disposal system in every county (city). Most importantly, the construction of medical waste disposal facilities must be capable of responding to emergencies.

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Conflicts of Interest: The authors declare no conflicts of interest.

Nomenclature

Symbol	Definition
DMU_0	The DMU under evaluation
$j = 1, \ldots J$	Number of $DMUs$
$i_1 = 1, \ldots I_1$	Number of undesirable inputs
$i_2 = 1, \ldots I_2$	Number of desirable inputs
$i = i_1 \cup i_2$	Number of inputs
$r_1 = 1, \ldots R_1$	Number of desirable outputs
$r_2 = 1, \ldots R_2$	Number of undesirable outputs
$r = r_1 \cup r_2$	Number of outputs
$i_1^F = 1, \ldots I_1^F$	Number of undesirable inputs in MWCS
$i_1^S = 1, \ldots I_1^S$	Number of undesirable inputs in MWTS
$i_1 = i_1^F \cup i_1^S$	Number of undesirable inputs, $i_1 = 1, \ldots I_1$
$i_2^F = 1, \ldots I_2^F$	Number of desirable inputs in MWCS
$i_2^S = 1, \ldots I_2^S$	Number of desirable inputs in MWTS
$i_2 = i_2^F \cup i_2^S$	Number of desirable inputs, $i_2 = 1, \ldots I_2$
$r_1^F = 1, \ldots R_1^F$	Number of desirable outputs in MWCS
$r_1^S = 1, \ldots R_1^S$	Number of desirable outputs in MWTS
$r_1 = r_1^F \cup r_1^S$	Number of desirable outputs, $r_1 = 1, \ldots R_1$
$r_2^F = 1, \ldots, R_2^F$	Number of undesirable outputs in MWCS
$r_2^S = 1, \ldots R_2^S$	Number of undesirable outputs in MWTS
$r_2 = r_2^F \cup r_2^S$	Number of undesirable outputs, $r_2 = 1, \ldots R_2$
d_{ix}^t	ith slack variables of input variable in year t
d_{rz}^t	rth slack variables of intermediate variable in year
d_{ry}^t	rth slack variables of output variable in year t
$d_{i_1^F}^t$	ith input shortfall in MWCS
$d_{i_2^F}^t$	ith input excess in MWCS
$d_{r_1^F}^t$	ith output shortfall in MWCS (ith input shortfall in MWTS)
$d_{r_2^F}^t$	ith output excess in MWCS
$d_{i_2^S}^t$	ith input excess in MWTS
$d_{r_1^S}^t$	ith input shortfall in MWTS
$d_{r_2^S}^t$	ith input excess in MWTS
x_{i0}^t	ith input of DMU_0 in year t
z_{r0}^t	rth output(input) of DMU_0 in year t
y_{r0}^t	rth output of DMU_0 in year t
$x_{i_1^F}^t$	ith undesirable input of DMU_j in MWCS
$x_{i_2^F}^t$	ith desirable input of DMU_j in MWCS
$z_{r_1^F}^t$	ith desirable output (undesirable input) of DMU_j in MWCS (MWTS)
$y_{r_2^F}^t$	ith undesirable output of DMU_j in MWCS
$x_{i_2^S}^t$	ith desirable input of DMU_j in MWTS
$y_{r_1^S}^t$	ith desirable output of DMU_j in MWTS
$y_{r_2^S}^t$	ith undesirable output of DMU_j in MWTS
λ_j^t	Determinant of best practices for DMU_0
$\overline{x}_{i_1^F}$	The maximum among the ith undesirable inputs in MWCS
$\underline{x}_{i_2^F}$	The minimum among the ith desirable inputs in MWTS
$\overline{x}_{i_1^S}$	The maximum among the ith undesirable inputs in MWCS
$\underline{x}_{i_2^S}$	The minimum among the ith desirable inputs in MWTS
$\underline{y}_{r_2^F}$	The minimum among the rth undesirable outputs in MWCS

$\overline{y}_{r_1^S}$	The maximum among the *r*th desirable outputs in MWCS
$\underline{y}_{r_2^S}$	The minimum among the *r*th undesirable outputs in MWTS

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