Benchmarking Correctional Facilities in the United States: An Undesirable Output Data Envelopment Analysis Model

C. Christopher Lee
Central Connecticut State University

Joseph Adamski
Central Connecticut State University

Soomin Park
Howard University

This study evaluated the operational efficiency of 741 U.S. correctional facilities using Data Envelopment Analysis (DEA) with five inputs and two outputs, including undesirable outputs like disciplinary reports. An undesirable-output DEA model identified 128 efficient and 616 inefficient facilities. Efficient benchmarks averaged 825 capacity, 36.3 years in age, 31 professional staff, 189 security staff, 898 inmates, 1,043 disciplinary reports, and $27.6 million in annual costs. Hypothesis testing revealed that GED, ESL, vocational training, and health services were associated with higher efficiency. The DEA model offers a valuable tool for policymakers to benchmark and improve correctional facility operations nationwide.

Keywords: correctional efficiency, DEA, undesirable output, prison benchmarking

INTRODUCTION

Correctional facilities in the United States face significant challenges as they operate under budgetary constraints while striving to achieve the dual goals of cost-effective management and inmate rehabilitation (Fox, 2024). Increasing incarceration rates have placed further strain on state and federal budgets, underscoring the need for optimized facility management that not only prioritizes security but also enhances rehabilitative outcomes to lower recidivism rates (Hollenbeak, *et al.*, 2015; Dulisse *et al.*, 2020). Recent research highlights that efficient management of correctional facilities is integral to both reducing operational costs and improving long-term outcomes for inmates, suggesting that a focus on rehabilitation may yield tangible improvements in efficiency and post-release success (Nyhan 2002; Hollenbeak, *et al.*, 2015).

One of the primary factors influencing the efficiency of correctional facilities is the rate of inmate recidivism. Facilities with high recidivism rates incur greater operational costs due to repeated incarceration and strain on resources. For instance, the Connecticut Department of Corrections reported that nearly 46% of former inmates are re-incarcerated within three years, underscoring the importance of programs that reduce reoffending by improving inmates' reintegration into society (Dept. of Corrections, 2014). Studies suggest that introducing comprehensive educational and vocational programs, alongside mental health services, can positively impact both operational efficiency and inmate outcomes, supporting a reduction in recidivism rates and associated costs (Esperian, 2010; Spelman, 2009). However, research linking these programmatic interventions directly to facility efficiency remains sparse, highlighting a gap that this study aims to address.

This research employs Data Envelopment Analysis (DEA), a proven method for measuring efficiency in multi-input and multi-output environments, to evaluate the performance of correctional facilities. DEA is especially useful in public sector analysis, where efficiency cannot be measured by profit alone but must incorporate a variety of inputs (e.g., staffing, costs) and outputs (e.g., inmate population, disciplinary incidents) (Cesaroni & Lamberti, 2014; Wu & Huang, 2003). By utilizing an undesirable output DEA model, this study also incorporates negative outcomes, such as recidivism and disciplinary reports, thereby providing a comprehensive view of facility performance that encompasses both operational success and rehabilitative effectiveness (Tobón, 2022; Rogge *et al.*, 2015). This approach allows for the benchmarking of correctional facilities, identifying both high-performing institutions that can serve as models and underperforming ones where policy interventions may be beneficial.

The primary objective of this study is to evaluate the efficiency of correctional facilities in the U.S. using key input variables (facility capacity, staffing, and operational costs) and output variables (inmate population and disciplinary reports). By analyzing undesirable outcomes such as recidivism, the study aims to provide actionable insights into how facility characteristics, including educational programs and security levels, correlate with efficiency. Additionally, the study examines the impact of variables such as three-strike laws and gender-specific facilities on efficiency scores, providing guidance for policymakers and administrators to optimize resources and enhance facility operations. In doing so, this research advances the application of DEA in correctional facility management, providing an essential framework for data-driven decision-making.

LITERATURE REVIEW

Correctional Facility Efficiency and Cost Implications

Recent research highlights that the operational costs and efficiency of correctional facilities are heavily influenced by staff allocation, facility utilization, and budgetary management (Rogge *et al.*, 2015). Studies by Legislative Analyst's Office. (2024) and Tobón (2022) reveal that facilities operating near capacity, with adequate staffing and preventive measures, demonstrate lower costs and higher security levels. A comprehensive analysis by Hennebel *et al.* (2017) on English prisons highlights the adverse effects of overcrowding, suggesting that efficiency could be achieved through better resource planning and effective facility design to accommodate fluctuating inmate populations.

Rehabilitation and Recidivism as Determinants of Efficiency

Efforts to lower recidivism rates through rehabilitation have shown mixed results across different correctional systems. A study by Maguire et al. (2023) emphasizes the effectiveness of mental health and counseling programs in reducing recidivism, while Hall (2015) suggest that educational programs can lead to positive behavioral changes, enhancing facility efficiency by reducing repeated incarceration. Furthermore, Smith (2020) emphasizes the cost-benefit aspect of integrating vocational training into prison programs, highlighting significant long-term savings for the public and improved outcomes for rehabilitated inmates.

Data Envelopment Analysis (DEA) in Correctional Efficiency Studies

Data Envelopment Analysis (DEA) has been widely applied in correctional settings to evaluate and enhance facility efficiency, especially by accounting for undesirable outputs such as recidivism. DEA serves as a robust methodology for assessing the performance of decision-making units (DMUs), such as correctional facilities, which accommodate multiple inputs and outputs. This approach is especially valuable in the public and non-profit sectors, where operational efficiency involves balancing complex dynamics. Correctional facilities utilize DEA to benchmark efficiency by comparing resources (inputs, such as staffing and capacity) against performance measures (outputs, such as inmate populations and participation in rehabilitation programs). For instance, Butler and Johnson (1997) used DEA to assess Michigan prisons, considering variables such as reported beds, expenditures, staff numbers, and rehabilitation participation rates. Hall *et al.* (2013) further demonstrated the role of DEA in identifying efficiency trends across correctional facilities, noting that disciplinary incidents and rehabilitation quality significantly influence efficiency outcomes. More recently, Tandfonline (2023) applied DEA in local prisons, showing that optimizing for minimal disciplinary incidents could enhance overall operational efficiency. This adaptability makes DEA well-suited for identifying both efficient and resource-intensive facilities, enabling data-driven improvements.

Traditional DEA models in correctional studies focus on constructing an efficiency frontier. Facilities that operate on this frontier are deemed efficient, while those below it are identified as inefficient and subject to further analysis for potential improvements. By comparing correctional facilities based on diverse inputs and outputs, DEA assessments extend beyond simple cost metrics to incorporate factors such as program participation rates, facility occupancy, and other attributes that reflect the operational dynamics within each facility. Facilities identified as inefficient through DEA can gain insight into potential enhancements, such as reallocating resources or adjusting program intensity, to improve their performance and align closer with the efficiency frontier.

In correctional settings, certain outcomes, such as disciplinary incidents and recidivism rates, are classified as "undesirable" due to their adverse effects on facility operations and overall outcomes. Incorporating these undesirable outputs into DEA models enables more nuanced assessments that emphasize rehabilitative outcomes while mitigating adverse factors. For instance, Cesaroni and Lamberti (2014) applied an undesirable output DEA model to Italian prisons and found that issues like overcrowding negatively impacted efficiency, whereas the integration of technological tools for monitoring positively influenced operational success. By including undesirable outputs, DEA models can reflect operational efficiency in ways that align with goals of rehabilitation and inmate reintegration, providing valuable insights for correctional administrators seeking to optimize facility performance.

This study employs a slack-based measure within an undesirable output DEA framework, incorporating "slacks" or excesses in undesirable outputs, such as high recidivism rates or frequent disciplinary incidents, and shortfalls in desirable outputs. This model offers a more comprehensive efficiency assessment, enabling administrators to pinpoint specific areas for improvement, such as implementing behavioral management programs or expanding vocational training, both of which can reduce recidivism and enhance overall efficiency. By using this approach, facilities can reduce undesirable outcomes while enhancing rehabilitative success.

DEA’s versatility has enabled it to be applied across a wide range of correctional contexts. Nyhan (2002) used DEA to evaluate juvenile correctional facilities in Florida, comparing the efficiency of publicly and privately managed halfway houses. This study highlighted how management structure influences facility efficiency, revealing differences in resource allocation and program implementation between public and private institutions. Similarly, Cesaroni and Lamberti (2014) suggested that integrating technology, such as electronic monitoring, could further enhance DEA’s capacity to measure efficiency in contemporary correctional settings, although quantifying these technological impacts remains challenging. Research by Carey (2018) on U.S. correctional education further supports the utility of DEA by linking effective education programs with reduced recidivism and improved overall facility efficiency. Likewise, Crowhurst and Harwich (2016) explored rehabilitative outputs in UK prisons, finding that DEA models incorporating rehabilitative measures offer a more refined view of efficiency, particularly when program outcomes align with the facilities’ operational goals. Together, these studies underscore DEA’s flexibility in correctional contexts and reinforce the value of incorporating rehabilitative and security-focused outputs in efficiency assessments.

DEA’s application in correctional facilities provides insights beyond traditional cost-focused analyses, as it considers various input-output relationships tied to rehabilitation and recidivism. Through DEA, administrators can make informed decisions on resource allocation, operational practices, and policy-making aimed at reducing re-incarceration rates and enhancing long-term inmate reintegration. This study builds upon prior research by applying an undesirable output DEA model to over 1,800 U.S. correctional facilities, taking into account variables such as facility age, capacity, staffing levels, and disciplinary incidents. The analysis offers a comprehensive efficiency assessment, identifies critical areas for operational improvement, and provides data-driven recommendations for policy and practice.

In summary, the DEA's adaptability makes it a powerful tool for evaluating the efficiency of correctional facilities. By analyzing how various facility characteristics, program offerings, and management styles impact operational success, DEA provides correctional administrators with valuable insights into optimizing resource utilization and enhancing rehabilitative outcomes. This methodology thus represents a critical asset for corrections policy and the broader goal of improving the efficacy and impact of correctional institutions.

Gaps in Literature and Study Contribution

Although studies highlight the impact of rehabilitation on correctional facility efficiency, few incorporate undesirable output DEA modeling with recidivism as a core factor (Ganley, 1989; Wu & Huang, 2003). This study addresses the gap by using DEA to analyze undesirable outputs in operational and rehabilitative efficiency, offering insights into best practices for optimizing resources across various facility types. By integrating rehabilitative programming data, this research provides a foundational model for future policy formulation aimed at reducing recidivism and enhancing operational efficiency.

HYPOTHESIS DEVELOPMENT

Correctional facilities with access to healthcare services benefit from reduced operational disruptions, as medical treatment helps address inmate health issues that would otherwise demand intensive resources. Hollenbeak *et al.* (2015) underscore that effective medical services lower health-related crises, contributing to smoother operations and enhanced efficiency. Spelman (2009) and Esperian (2010) similarly emphasize that when facilities offer health services alongside educational programs, the combination can further reduce recidivism and improve operational outcomes, which collectively enhance efficiency.

Hypothesis #1: *If a correctional facility offers medical treatment, then it will have a higher efficiency score.*

Educational programs within correctional facilities have a significant impact on recidivism rates by equipping inmates with skills for post-release success, thereby improving operational efficiency. Recent studies, such as those by Berglund et al. (2025), confirm that inmate education reduces disciplinary incidents, alleviating operational strain and contributing to overall efficiency gains. Studies by Spelman (2009) and Esperian (2010) suggest that educational programs can foster improved inmate behavior, thereby reducing resource demands and supporting a stable operational environment.

Hypotheses #2-8: *If a correctional facility offers various adult educational programs, then it will have a higher efficiency score.*

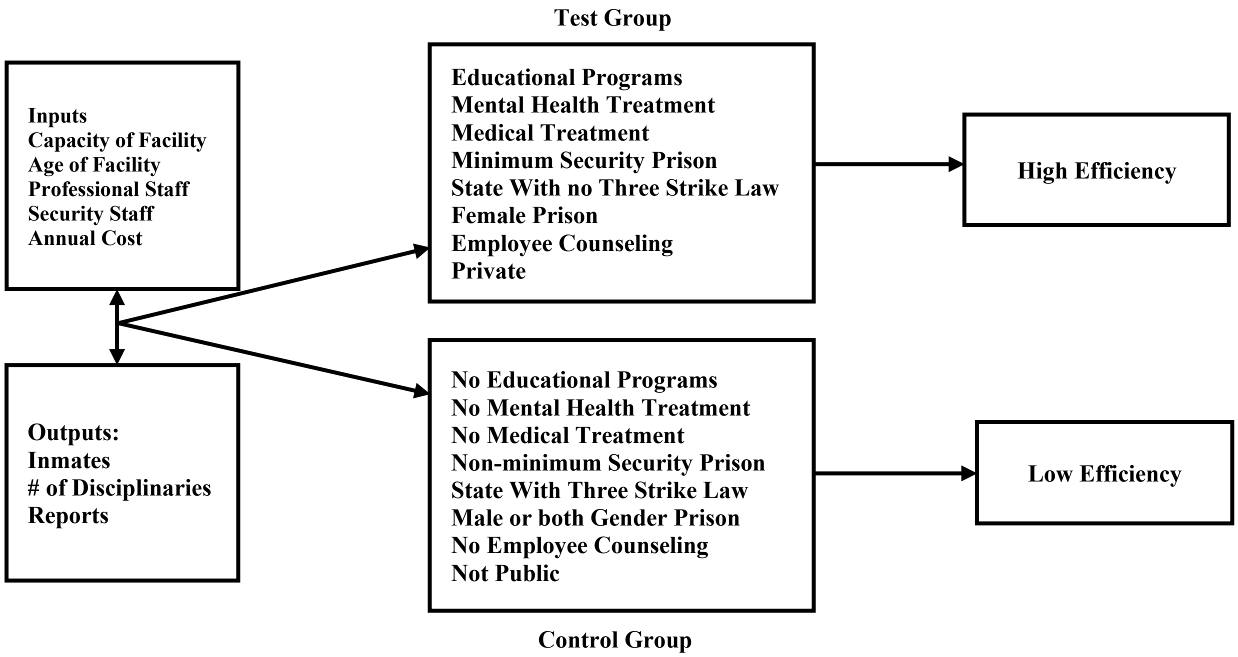
Mental health services in correctional settings play a critical role in reducing disruptive behavior, thereby stabilizing facility operations. Smith and Roberts (2023) highlight that mental health support minimizes the occurrence of self-harm and aggression, contributing to more efficient operations. Beaudry *et al.* (2021) and Maguire *et al.* (2023) also report that mental health care in facilities helps mitigate violent disturbances, further enhancing efficiency by reducing the need for frequent security interventions.

Hypothesis #9: *If a correctional facility offers mental health treatment, then it will have a higher efficiency score.*

While research on the efficiency of private versus public facilities varies, the Cicero Institute. (2024) suggests that private facilities may achieve higher efficiency through streamlined management. However, a study by the Prison Policy Initiative (2025) offers a contrasting view, suggesting that efficiency gains in private facilities may sometimes come at the expense of program quality. This hypothesis posits that private facilities may demonstrate higher efficiency due to their operational focus on cost reduction; however, the effectiveness of these efficiencies requires a balanced consideration.

Hypothesis #10: *If a correctional facility is a private correctional facility, then it will have a higher efficiency score.*

FIGURE 1
RESEARCH FRAMEWORK



Facilities with minimum security generally incur lower per-inmate costs due to reduced security demands. Jacobson (2006) notes that non-violent offenders in minimum-security settings typically require fewer resources, which enhances operational efficiency. Steiner (2009) further notes that facilities with lower security levels tend to experience fewer violent incidents, which contributes to resource optimization and potentially higher efficiency scores.

Hypothesis #11: *If a correctional facility is a minimum-security correctional facility, then it will have a higher efficiency score.*

Counseling services for correctional employees are crucial for improving job performance and reducing turnover in high-stress environments. Oruru (2024) finds that staff counseling enhances employee well-being, resulting in higher productivity and efficiency. Spelman (2009) and Smith and Roberts (2023) similarly suggest that employee mental health support can mitigate stress-related conflicts, benefiting both the work environment and facility efficiency.

Hypothesis #12: *If a correctional facility offers counseling to its employees, then it will have a higher efficiency score.*

Three-strike laws are known to increase prison populations and strain resources, leading to reduced facility efficiency. Berkeley School of Public Policy (2025) finds that states without three-strike laws often experience lower recidivism and smaller inmate populations, both of which support efficient facility operations. Sutton (2013) also highlights the deterrent effect of such laws, noting that while they may reduce crime, the resulting population growth in facilities can undermine operational efficiency.

Hypothesis #13: *If a correctional facility is in a state without three-strike laws, then it will have a higher efficiency score.*

Research consistently shows that female correctional facilities experience fewer violent incidents, resulting in less resource strain and higher efficiency. Towns, Ricciardelli, and Spencer (2024) observe that female facilities generally require fewer interventions, which supports operational stability and allows for a more efficient allocation of resources. Wright and Cain (2018) also found that lower violence rates in female facilities contribute to smoother operations and improved efficiency.

Hypothesis #14: *If a correctional facility is a female correctional facility, then it will have a higher efficiency score.*

MODEL DEVELOPMENT

Input Variables

The study examines several key input variables essential for evaluating the efficiency of correctional facilities. Each variable reflects resources or structural characteristics that impact both performance and costs. ***Capacity of facility*** is a primary input variable, as facilities with different capacities demonstrate varying operational efficiencies often due to disparities in resource allocation and management strategies (Wu & Huang, 2003). Facilities designed with appropriate capacity management can optimize staffing, program offerings, and other resources to maintain a balanced operational environment. Another input variable, ***age of facility***, influences efficiency considerably; newer facilities typically incorporate modern technology and infrastructure improvements, which can reduce maintenance costs and enhance efficiency (Vitner *et al.*, 2006). Older facilities, on the other hand, may have higher costs due to outdated designs and equipment, which may negatively impact operational performance.

Professional staff count is also a significant input factor, as staffing levels directly influence the resource allocation and quality of inmate care. Well-managed staffing strategies often lead to higher efficiency levels by reducing unnecessary labor costs and ensuring adequate support for rehabilitation programs (Baharudin, 2022). Similarly, ***security staff count*** affects both safety and resource expenditure within a facility. Facilities that maintain optimal security staffing can ensure effective monitoring and control while avoiding overstaffing, which may inflate operational costs (Alda, 2022). Lastly, ***annual operational cost*** is a critical input variable, with lower operational costs generally linked to higher efficiency. Effective resource management that minimizes per-inmate expenses is closely aligned with DEA's efficiency objectives, demonstrating that cost-effective operations contribute to the overall success of facility management (Banker *et al.*, 2019).

Output Variables

The output variables in this study measure operational effectiveness, with a focus on minimizing undesirable outcomes. ***Inmate population*** is a key output variable as it directly influences resource allocation. Facilities that effectively manage larger inmate populations without sacrificing program quality or security measures exhibit enhanced efficiency. DEA modeling accounts for this factor, recognizing that resource demands fluctuate with population size, as seen in efficiency assessments of jails and prisons

(Sousa *et al.*, 2021). Another crucial output variable is ***disciplinary reports***, with higher rates of incidents considered undesirable outputs that reflect operational strain and potential inefficiencies. By incorporating disciplinary data, DEA modeling offers a comprehensive view of how frequent incidents may indicate areas where resource reallocation or policy adjustments could enhance efficiency (Örkcü *et al.*, 2016).

Control Variables

To capture the broader programmatic and environmental influences on facility efficiency, several control variables are included in this study. ***Educational programs***, such as GED, ESL, and adult education classes, have been linked to higher post-release success rates, ultimately reducing recidivism and enhancing overall efficiency within facilities (Alda, 2019). Similarly, ***vocational training*** plays a crucial role in equipping inmates with employable skills, thereby reducing the likelihood of reoffense upon release and contributing positively to efficiency scores (Sherman & Zhu, 2006). Access to ***medical and mental health* services** is also significant, as these services contribute to inmate stability, reduce health-related incidents, and support an efficient operational environment (De Sousa *et al.*, 2005).

Management style is another important control variable. ***Private versus public facility management*** can influence efficiency scores due to operational differences between the two models. Private facilities, for instance, may prioritize cost-saving measures differently than public facilities, which can impact efficiency outcomes (Vitner *et al.*, 2006). The ***security level*** of a facility is also relevant; minimum-security facilities typically require fewer resources per inmate compared to maximum-security institutions, thereby impacting efficiency in terms of resource allocation and program intensity (Golany & Storbeck, 2019). Finally, ***three-strike laws*** affect facility dynamics by indirectly influencing recidivism rates. States that enforce three-strike laws may experience higher or lower inmate turnover rates based on the severity of sentences, which in turn affects population management and operational efficiency (Vitner *et al.*, 2006).

DEA Model

This research employs Data Envelopment Analysis (DEA) to calculate an efficiency value for each correctional facility. DEA is an effective method for measuring relative efficiency among comparable organizations, making it a suitable tool for analyzing correctional facilities. In this context, each facility being evaluated in terms of efficiency is referred to as a decision-making unit (DMU). The DEA model identifies the most efficient DMUs, setting them as benchmarks, while less efficient units are rated against these exemplary standards.

The DEA model has been applied in other studies to assess efficiency within the public sector and nonprofit entities. A study conducted by Butler and Johnson (1997) utilizes the DEA model, highlighting DEA as an innovative approach compared to traditional analytical tools for measuring efficiency. The DEA model systematically covers data to identify relationships within the dataset, facilitating a holistic efficiency assessment. According to Butler and Johnson (1997), the DEA model offers an overall evaluation of relative efficiency by identifying exemplary correctional facilities and pinpointing specific areas for improvement within less efficient units. However, DEA does not provide insights into the reasons behind an area or unit's inefficiency, leaving these factors to be analyzed separately.

Multiple studies have employed DEA to understand the efficiencies of the correctional facility system. Butler and Johnson (1997) employed the DEA model to analyze efficiency, selecting the reported number of beds, number of employees, and expenditures as input variables, while using the number of prisoners and participation in rehabilitation programs as output variables. This study concluded that the DEA model accurately measures efficiency and is more cost-effective than other alternatives. Nyhan (2002) conducted a similar study and found DEA to be effective in measuring efficiency among juvenile correctional facilities, thus further supporting the suitability of DEA for the corrections sector.

Cesaroni and Lamberti (2014) also utilized DEA to quantify the efficiency of correctional facilities. Their study employed a larger dataset than previous studies, similar to the dataset used in this research, which includes approximately 1,800 correctional facilities. Cesaroni and Lamberti (2014) found DEA effective for analyzing the “complex” systems that constitute correctional facilities. They observed that overcrowding had the most significant negative impact on efficiency, while the integration of technology exerted the largest positive effect.

Model Specification

In a modern society, there are often outputs that want to be minimized due to legal or ethical concerns. For instance, in our study, the number of disciplinary reports has a negative effect; the more of them there are, the more it increases. Due to this, our group employed an undesirable output DEA model, which measures efficiency by using the least amount of resources to produce the highest amount of good outputs while keeping the bad outputs low. The software we employed uses a slacks-based measure of efficiency which is a model that utilizes input and output slacks directly in producing an efficiency measure (Tone, 2001).

Below is an excerpt taken from the software manual explaining the implementation of the undesirable output model we utilized (Saitech Inc.):

Let us decompose the output matrix Y into (Y^g,Y^b) where Y^g and Y^b denote good (desirable) and bad (undesirable) output matrices, respectively. For a DMU (X_0, Y_0), the decomposition is denoted as (X_0,$Y^g{}_o$$Y^b{}_o$).

We consider the production possibility set defined by:

$$P = \{(x, y^g, y^b) \mid x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda, L \leq e\lambda \leq U, \lambda \geq 0\}$$

[Definition 1] (Efficient DMU)

A DMU is (X_0,$Y^g{}_o$,$Y^b{}_o$) is efficient in the presence of bad outputs, if there is no vector (x,y_g,y_b) ∊ P such that x_0 >= X, $Y^g{}_o$ <= y^g , $Y^b{}_o$ >= y^b with at least one strict inequality. In accordance with this definition we modify the SBM in Tone (2001) as follows:

The vectors s^- and s^b correspond to excesses in inputs and bad outputs, respectively, while s^g expresses shortages in good outputs. s_1 and s_2 denote the number of elements in s_b and s_g and $s = s_1 + s_2$. Let an optimal solution, of the above program be (p^*, s^{-*},s^{g*},s^{b*}). Then we can demonstrate that the DMU (X_0,$Y^g{}_o$,$Y^b{}_o$) is efficient in the presence of undesirable outputs if and only if $p^* = 1$. If the DMU, is inefficient, i.e., $p^* < 1$, it can be improved and become efficient by deleting the excesses in inputs and bad outputs and augmenting the shortfalls in good outputs by the following projection:

$$\begin{aligned} x_o &\Leftarrow x_o - s^{-*} \\ y_o^g &\Leftarrow y_o^g + s^{g^*} \\ y_o^b &\Leftarrow y_o^b - s^{b^*}. \end{aligned}$$

The above fractional program can be transformed into an equivalent linear program by using Charnes-Cooper transformation (see Tone (2001) for details). By considering the dual side of the linear program, we have the following dual program in the variable v,u^g,u^b for the CRS case, i.e. L = 0, U = infinity: (Refer to Tone (2001) for derivation).

$$max\ u^g y_o^g - v x_o - u^b y_o^b$$

subject to

$$u^g Y^g - vX - u^b Y^b \leq 0$$
$$v \geq \frac{1}{m}[1/x_o]$$
$$u^g \geq \frac{1 + u^g y_o^g - v x_o - u^b y_o^b}{s}[1/y_o^g]$$
$$u^b \geq \frac{1 + u^g y_o^g - v x_o - u^b y_o^b}{s}[1/y_o^b]$$

The dual variables v and u^b can be interpreted as the virtual prices (costs) of inputs and bad outputs respectively, while u^g denotes the price of good outputs. The above dual program aims to obtain the optimal virtual costs and prices for the DMU, ensuring that the profit does not exceed zero for every DMU and maximizes the profit for the DMU concerned. The optimal profit is at best zero and identifies the DMU as efficient.

In the BadOutput model, we set the weights to bad and good outputs through keyboard before running the model. If we supply w_1 (>= 0) and w_2 (>= 0) as the weights to good and bad outputs, respectively, then the model calculates the relative weights as $W_1 = sw_1/(w_1 + w_2)$ and $W_2 = sw_2/(w_1 + w_2)$, the objective function will be modified to:

$$\rho^* = min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_{io}^-}{x_{io}}}{1 + \frac{1}{s}\left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{ro}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{y_{ro}^b}\right)}$$

subject to

$$\begin{aligned} x_o &= X\lambda + s^- \\ y_o^g &= Y\lambda - s^g \\ y_o^b &= Y\lambda + s^b \\ L \le e&\lambda \le U \\ s^-, s^g&, s^b, \lambda \ge 0 \end{aligned}$$

Data Collection

The dataset utilized in the DEA model originates from a census of correctional facilities conducted by the Bureau of Justice Statistics (BJS) (http://www.bjs.gov/index.cfm?ty=dcdetail&iid=255). This comprehensive dataset gathers detailed information on various aspects, such as types of inmates, facility age, security levels, court orders, operational details, confinement space, and staff characteristics. The dataset's scope is extensive, encompassing both private and public correctional facilities to include as many respondents as possible. Initially, the dataset consisted of approximately 1,800 respondents from correctional facilities before data cleaning.

However, the most recent dataset available is from 2005, which presents limitations due to its age. Although the Bureau of Justice typically conducts this census every five to seven years, budget constraints have prevented an update since 2005. The BJS provides a codebook with the dataset to clarify the meaning of each variable and indicate missing values. Notably, the 2005 dataset had missing data for several variables essential to this study. Out of the complete dataset of 1,821 correctional facilities, only 741 remained after eliminating entries with missing values and reducing variables not relevant to this study. The data cleaning process involved removing irrelevant variables, followed by eliminating rows with incomplete input or output variable data, resulting in a refined dataset where all values for input and output variables were fully populated.

During this study, the Bureau of Justice was contacted, and they confirmed that they did not anticipate releasing an updated census until 2017. This research could serve as a foundation for future studies analyzing the next dataset when it becomes available.

RESULTS

Descriptive Statistics

After cleaning the collected data, a total of 741 correctional facilities in the United States remained in the dataset. Table 1 below presents the minimum and maximum values for each input and output variable. The variation between these ranges is substantial, so we also calculated the mean and standard deviation to account for the variability in each variable. This approach helps to ensure minimal imbalance within the dataset.

TABLE 1
DESCRIPTIVE STATISTICS FOR INPUT AND OUTPUT VARIABLES

Variable	N	Minimum	Maximum	Mean	Std. Deviation
Capacity (I)	741	19	5108	822.1	771.2
Age (I)	741	0	188	36.4	34.2
Professional Staff (I)	741	1	216	30.8	31
Security Staff (I)	741	1	1336	188.8	182.1
Annual Cost (I)	741	335869	185004780	27468150	28856781
Inmates (O)	741	14	5499	894.7	824.9
Disciplinary Reports (O)	741	0	9302	1039.6	1543.5

Table 2 presents the cleaned sample data for a total of 741 correctional facilities in the United States, representing the combined results of the Control Group (No) and the Test Group (Yes). The table shows the distribution of individual control variables within the dataset. The Control Group (No) column shows the number of facilities that did not implement the control variable, while the Test Group (Yes) column shows the number of facilities that did. The data indicates that over 75% of correctional facilities in our sample provide either Adult Education, Employment Counseling, Literacy Training, or GED courses.

TABLE 2
DESCRIPTIVE STATISTICS FOR INPUT AND OUTPUT VARIABLES

Hypothesis	Control Variables	Description of Control Variable	# of Prisons Control Group (No)	# of Prisons Test Group (Yes)
1	Onsite Medical Treatment	Facility offers onsite medical treatment.	653 (88.1%)	88 (11.9%)
2	Adult Education	Facility offers adult education programs.	181 (24.4%)	560 (75.6%)
3	Literacy Training	Facility offers a literacy training program.	180 (24.3%)	561 (75.7%)
4	GED Courses	Facility offers GED courses.	94 (12.7%)	647 (87.3%)
5	Special Education Programs	Facility offers special education programs.	530 (71.5%)	211 (28.5%)
6	English as a Second Language	Facility offers English as a second language course.	509 (68.7%)	232 (31.3%)
7	College Courses	Facility offers college courses.	459 (61.9%)	282 (38.1%)
8	Vocational Training	Facility offers a vocational training program.	298 (40.2%)	443 (59.8%)
9	Mental Health Treatment	Facility offers mental health treatment.	658 (88.8%)	83 (11.2%)
10	Private Prison	Facility is a private prison.	630 (85.1%)	111 (14.9%)

11	Security Level of Facility	Facility is minimum security.	405 (55.2%)	328 (44.8%)
12	Employment Counseling	Facility offers an employment counseling program.	181 (24.4%)	560 (75.6%)
13	3 Strike Law	Facility has 3 strike law.	460 (62.1%)	281 (37.9%)
14	Gender Housed	Facility is female housed.	673 (90.8%)	68 (9.2%)

Correlation Analysis

The Spearman's Rank Correlation coefficient (ρ) in Table 3 below is a nonparametric measure of the strength of association between two ranked variables. It is used to support or challenge a hypothesis. We analyzed the inputs and outputs to determine their relationship with undesirable efficiency factors. The variable *Input Age* shows a negative correlation, indicating that as the age of the facility decreases, efficiency increases. Both *Input Professional Staff* and *Input Security Staff* also display negative correlations, suggesting that as staff numbers decrease, efficiency improves.

Additionally, *Input Annual Cost* shows a negative correlation, meaning that as annual costs decrease, efficiency rises. The variable *Output Inmates* presents a positive correlation, signifying that as the number of inmates decreases, efficiency improves. However, *Input Capacity* and *Output Inmates* do not demonstrate statistically significant relevance to our data analysis.

There is a multicollinearity issue between *Output Inmates*, *Output Bad Disciplinarians*, and *Input Capacity*. Ideally, our model should avoid any interrelationships among inputs to ensure accuracy. This multicollinearity suggests potential inaccuracies in the data, implying that the statistical hypotheses based on this data may not be entirely reliable.

Using DEA modeling, we analyzed the input and output variables to generate an efficiency value for each of the correctional facilities. Figure 2 displays each state's average efficiency score, with states color-coded on a gradient from zero efficiency (white) to an efficiency of 1 (dark green). States with no available data are left in white. As the efficiency score increases, the shade of green darkens, with the darkest shade representing scores closest to 1. A few states achieved high efficiency scores; for example, Kentucky scored 0.915, while Alabama and Indiana scored 0.8584. Conversely, some states exhibited low efficiency scores, with New York at 0.2638 and Rhode Island at 0.2644.

TABLE 3
CORRELATION ANALYSIS

	E_Undesirable	iCapacity	iAge	iProfStaff	iSecurityStaff	iAnnualCost	oInmates	oBadDisciplinaries
E_Undesirable	1							
iCapacity	0.008	1						
iAge	-0.321**	-0.135**	1					
iProfStaff	-0.229**	0.795**	0.000	1				
iSecurityStaff	-0.193**	0.886**	-0.002	0.839**	1			
iAnnualCost	-0.155**	0.888**	-0.03	0.857**	0.929**	1		
oInmates	0.067	0.963**	-0.094*	0.813**	0.904**	0.931**	1	
oBadDisciplinaries	-0.258**	0.660**	-0.064	0.519**	0.651**	0.626**	0.659**	1

N=741
*** correlation is significant at the 0.01 level*
** correlation is significant at the 0.05 level*

FIGURE 2
GEOGRAPHIC MAP OF AVERAGE EFFICIENCIES

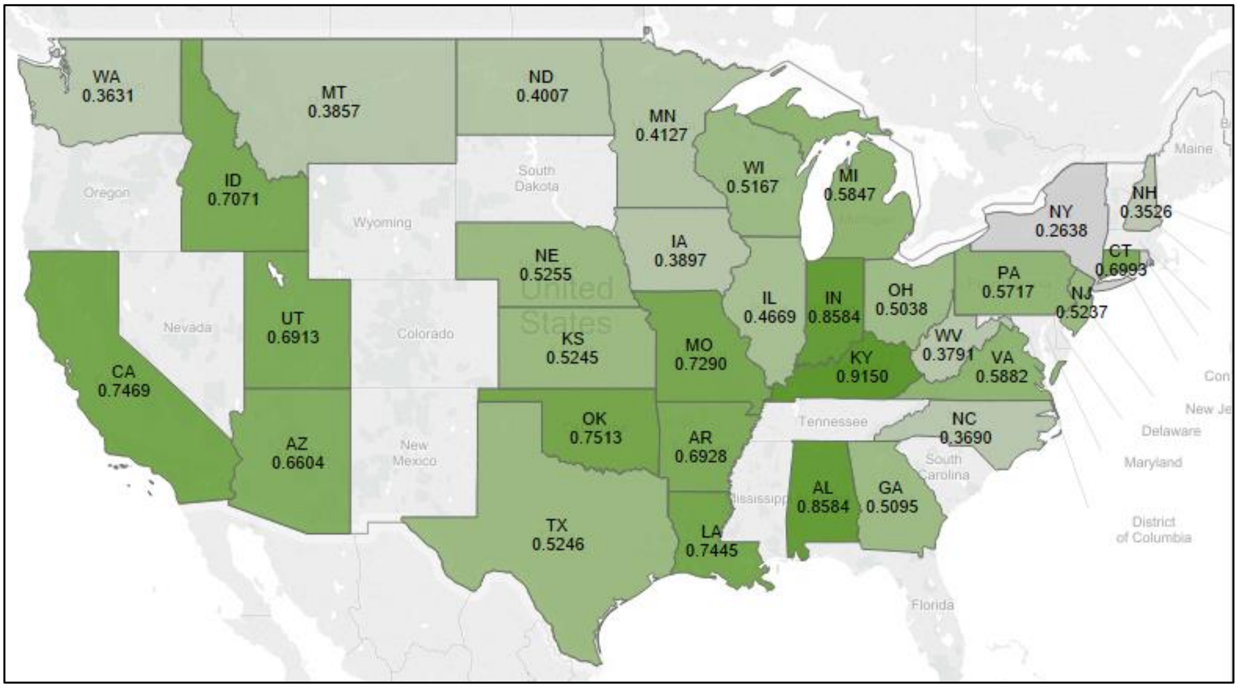


Figure 3 below presents the 30 highest benchmark correctional facilities with efficiency scores below 1. Policymakers can examine these facilities to identify common programs that contribute to higher efficiency. By implementing similar programs in lower-performing facilities, policymakers can potentially increase efficiency and reduce costs in correctional facilities.

Figure 4 highlights the 30 correctional facilities with the lowest efficiency scores. These facilities require the most attention from policymakers seeking to reduce correctional facility costs.

Figure 5 displays the average efficiency score for each state included in the cleaned dataset. Kentucky correctional facilities have the highest average efficiency score at 0.9150, while New York has the lowest at 0.2638. This visualization suggests that states such as New York, Rhode Island, and New Hampshire may benefit from examining the practices of higher-performing states like Kentucky, Indiana, or Alabama. Interestingly, the three least efficient states are all located in New England, indicating that geographic location in the Northeast may play a role in influencing costs and efficiency.

FIGURE 3
TOP 30 NON-BENCHMARK FACILITIES

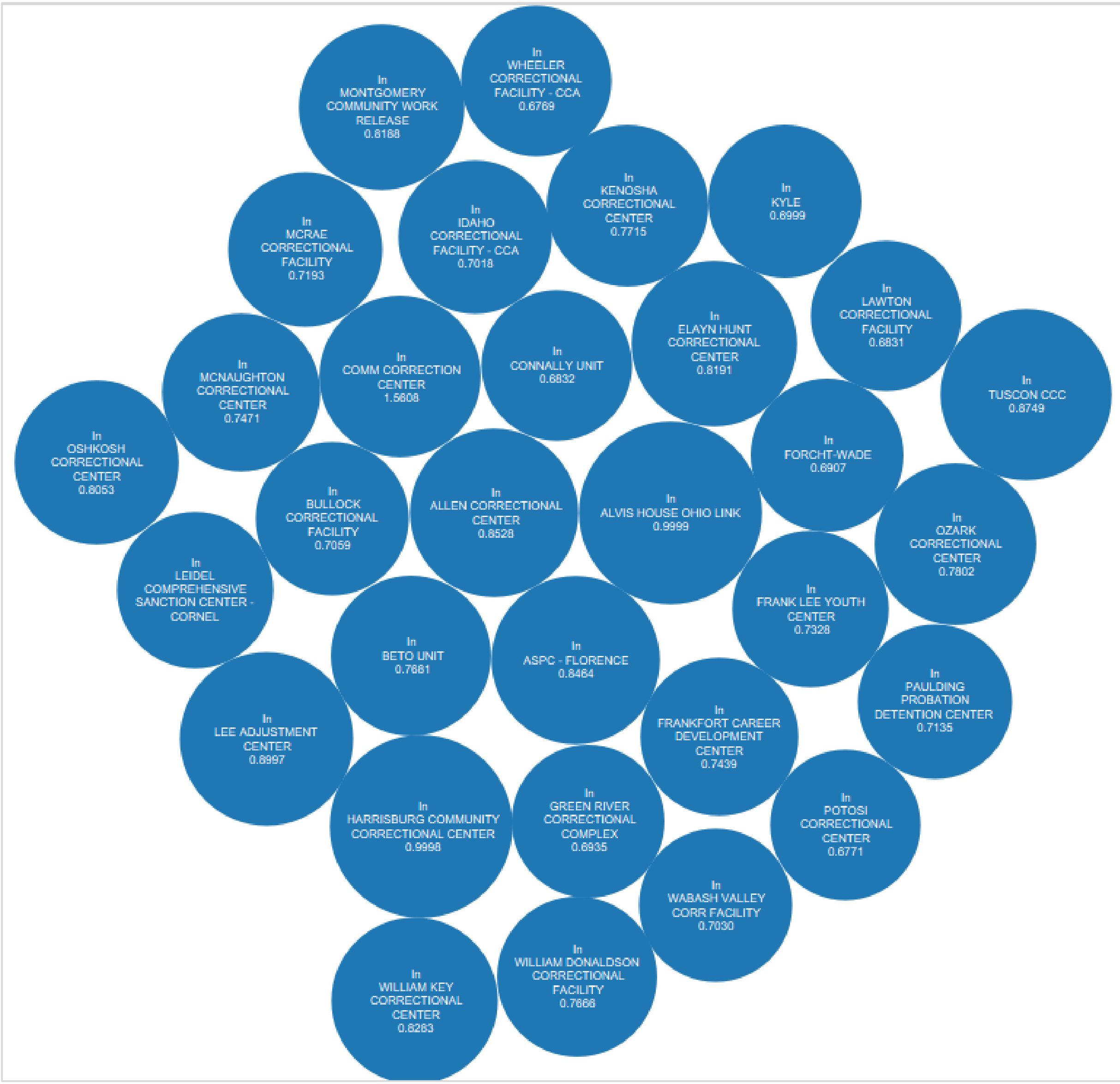


FIGURE 4
LOWEST EFFICIENCY FACILITIES

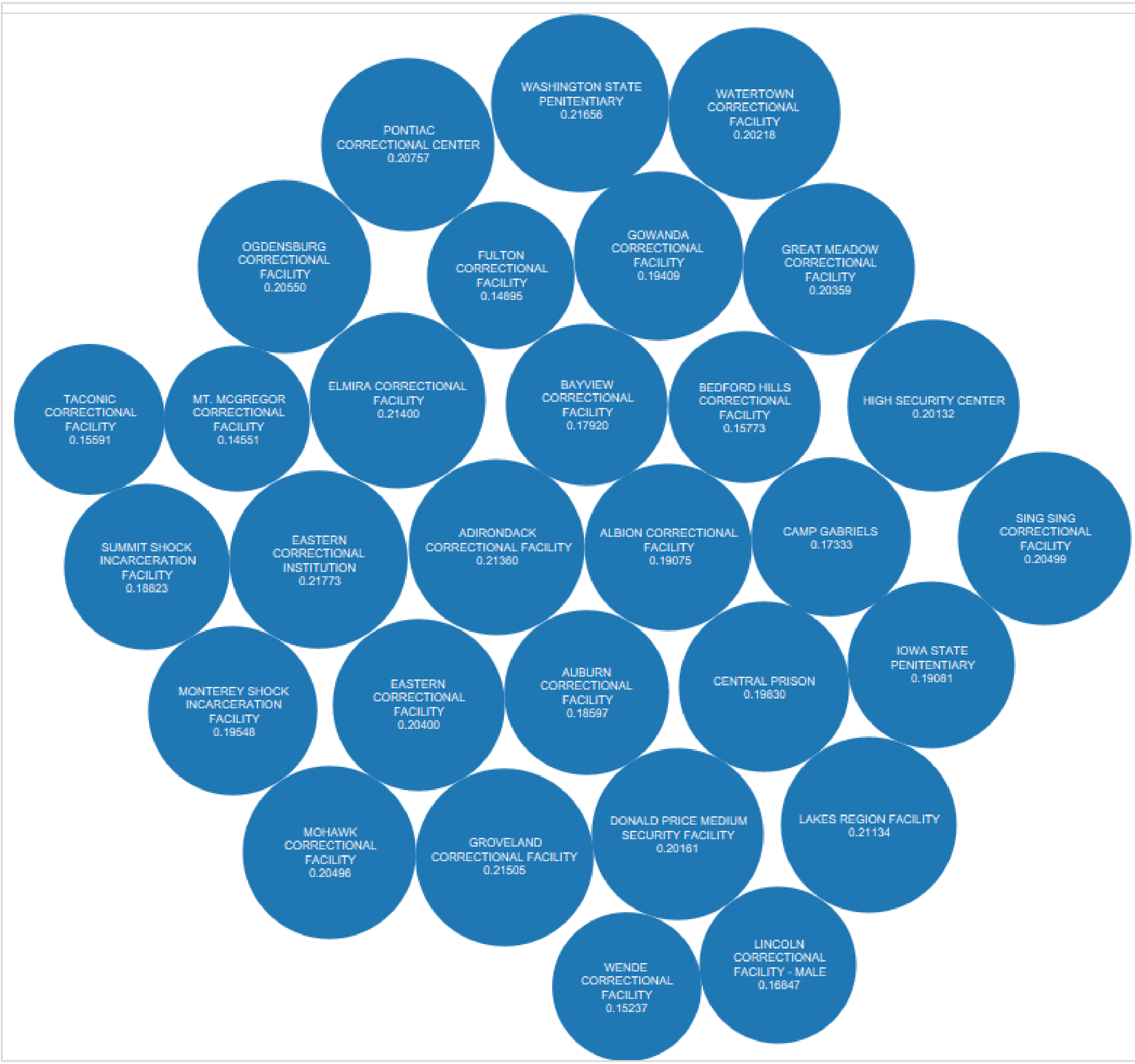


FIGURE 5
AVERAGE EFFICIENCIES BY STATE

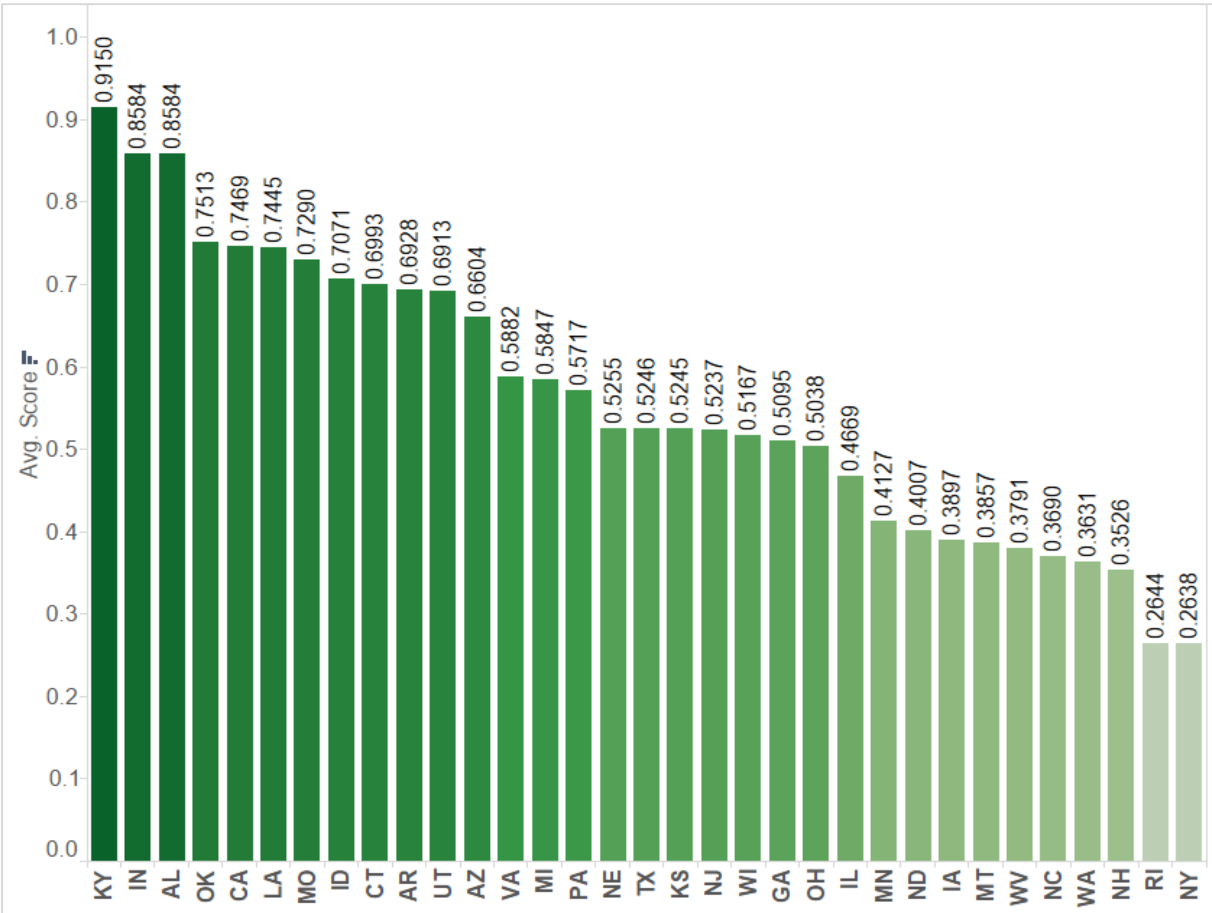


Figure 6 displays the top 30 correctional facilities with the highest annual average costs. ASPC - Florence in Arizona had the highest annual cost at $96,739,500, while Alvis House Ohio Link in Ohio had the lowest at $40,466. Policymakers can use this information to identify facilities with the highest costs and compare them to similarly sized facilities with lower costs.

The Mann-Whitney U test was then employed to determine whether there is a correlation between the efficiency value and each of the grouping variables. Table 4 below presents the actual significance value (p-value) of the Mann-Whitney U test, with a significance level of 0.05.

FIGURE 6
MOST EXPENSIVE FACILITIES

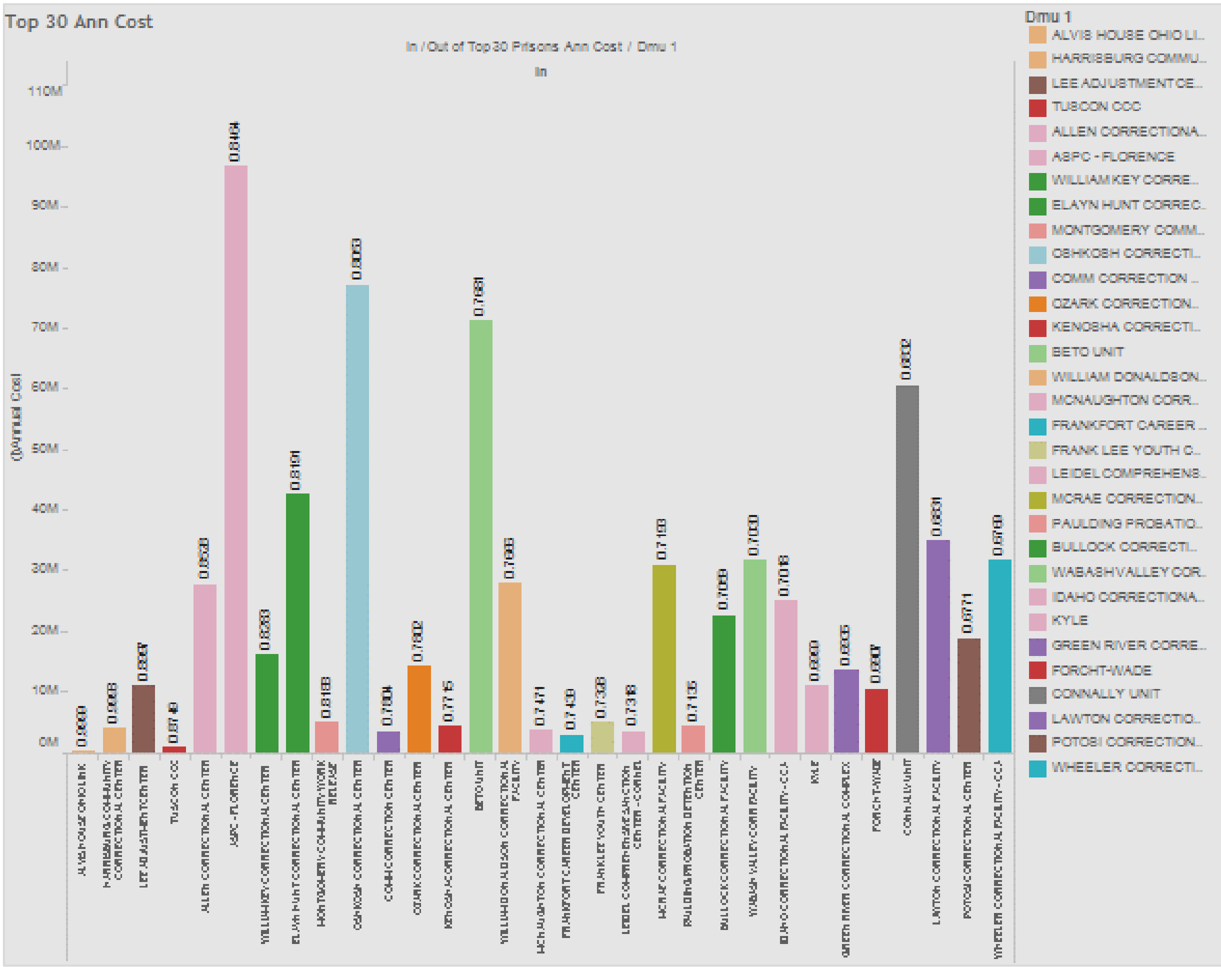


TABLE 4
RANKING BASED ON CONTROL GROUPS AND MANN-WHITNEY U RESULTS

Hypothesis	Control Variable	Control Group Mean Ranking	Test Group Mean Ranking	Mann-Whitney U	Standardized Test Statistic	P Value
1	Onsite Medical Treatment	382.91	282.66	20958.0	-4.135	0.000
2	Adult Education	402.86	360.70	44913.5	-2.309	0.0105
3	Literacy Training	408.06	359.11	43810.0	-2.677	0.0035
4	GED Courses	419.77	363.91	25824.5	-2.370	0.0178
5	Special Education Programs	367.07	380.87	57998.5	0.794	0.2140
6	English as a Second Language	394.79	318.80	46934.0	-4.493	0.0000
7	College Courses	373.87	366.17	63357.0	-0.483	0.3150
8	Vocational Training	398.83	352.28	57714.0	-2.910	0.0020

9	Mental Health Treatment	380.24	297.75	21227.5	-3.317	0.0005
10	Private Prison	349.41	493.56	48569.5	6.559	0.0000
11	Security Level of Facility	344.17	404.05	78867.0	3.797	0.0000
12	Employment Counseling	392.60	364.02	46770.5	-1.566	0.0600
13	3 Strike Law	383.66	350.27	58805.0	-2.066	0.0195
14	Gender Housed	373.59	345.35	21137.5	-1.040	0.1490

Hypothesis #1: The p-value is < 0.001, indicating a very strong statistical significance between efficiency and whether a correctional facility provides onsite medical treatment. Facilities with onsite medical treatment have a mean efficiency ranking of 282.66, compared to 382.91 for those that do not. Thus, our hypothesis is supported: offering onsite medical treatment enhances a correctional facility's efficiency ranking.

Hypothesis #2: The p-value of 0.0105 (0.021/2) indicates a strong statistically significant relationship between offering adult education in a correctional facility and its efficiency. Facilities with adult education have a mean efficiency ranking of 360.70, whereas those without such programs have a mean ranking of 402.86. This supports our hypothesis that adult education increases a facility's efficiency ranking.

Hypothesis #3: The p-value of 0.0035 (0.007/2) suggests a statistically significant relationship between literacy training and efficiency. Facilities with a literacy training program have a mean efficiency ranking of 359.11, compared to 408.06 for those without. Therefore, our hypothesis is confirmed, indicating that literacy training enhances a correctional facility's efficiency.

Hypothesis #4: The p-value of 0.009 (0.018/2) shows a statistically significant relationship between offering GED programs in correctional facilities and their efficiency. Facilities with a GED program have a mean efficiency ranking of 363.91, while those without have a ranking of 419.77. This confirms our hypothesis that GED programs improve a facility's efficiency ranking.

Hypothesis #5: The p-value of 0.214 (0.427/2) indicates no statistical significance between offering special education programs and mean efficiency ranking. Therefore, our hypothesis is not supported; special education programs do not significantly increase the efficiency ranking.

Hypothesis #6: The p-value is < 0.001, demonstrating a statistically significant relationship between offering English as a Second Language (ESL) classes in a correctional facility and its efficiency. Facilities with ESL classes have a mean efficiency ranking of 318.80, compared to 394.79 for those without. Thus, our hypothesis is supported, showing that ESL classes improve a correctional facility's efficiency ranking.

Hypothesis #7: The p-value of 0.315 (0.629/2) shows no statistical significance between efficiency scores and whether a correctional facility offers college courses. Therefore, our hypothesis is not supported, indicating that college courses do not increase the efficiency ranking.

Hypothesis #8: The p-value of 0.002 (0.004/2) suggests that vocational training is statistically significant and affects the efficiency of correctional facilities. Facilities with vocational training have a mean efficiency rank of 352.28, while those without have a rank of 398.83. Thus, our hypothesis is confirmed: facilities offering vocational training are more likely to achieve a higher efficiency ranking.

Hypothesis #9: The p-value is < 0.001 (0.001/2), indicating that mental health treatment is highly statistically significant and influences the efficiency of correctional facilities. Facilities offering mental health treatment have a mean efficiency rank of 297.75, while those without have a rank of 380.24. This supports our hypothesis that facilities offering mental health treatment are more efficient.

Hypothesis #10: The p-value is < 0.001, suggesting a very statistically significant relationship between private versus non-private management and correctional facility efficiency. Privately operated facilities have a mean efficiency rank of 493.56, while non-private facilities have a mean rank of 349.41. This refutes our hypothesis, as private facilities are unlikely to be more efficient than non-privately operated ones.

Hypothesis #11: The p-value is < 0.001, indicating that security level is highly statistically significant and affects correctional facility efficiency. Facilities with minimal security have a mean efficiency score of

404.05, compared to 344.17 for non-minimal security facilities. This finding does not support our hypothesis; non-minimal security facilities are more likely to be efficient than minimal-security ones.

Hypothesis #12: The p-value of 0.06 (0.117/2) indicates no statistical significance between employment counseling offered in correctional facilities and efficiency ranking. Therefore, our hypothesis is not supported; employment counseling does not significantly improve efficiency.

Hypothesis #13: The p-value of 0.0195 (0.039/2) suggests a statistical significance between the presence of three-strike laws in a state and correctional facility efficiency. Facilities in states with three-strike laws have a mean efficiency rank of 350.27, while those in states without these laws have a mean rank of 383.66. This supports our hypothesis that the three-strike law is associated with increased efficiency in correctional facilities.

Hypothesis #14: The p-value of 0.149 (0.298/2) indicates no statistical significance between efficiency scores and the gender housed in the correctional facility. Thus, our hypothesis is not supported; female correctional facilities do not show a significant increase in efficiency ranking.

TABLE 5
QUARTILE PERFORMANCE

Variable	Benchmark (E=1) n=128	1st Quartile n=154 (0.51773<0.99988)	2nd Quartile n=154 (0.40642<0.51742)	3rd Quartile n=152 (0.32143<0.40638)	4th Quartile n=154 (0.14551<0.32001)
(I) Capacity	824.73	1098.94	773.18	674.13	701.86
(I) Age	36.29	28.4	26.12	38.41	58.42
(I) Professional Staff	29.68	28.81	25.58	29.87	38.62
(I) Security Staff	189.28	201.83	151.18	178.72	241.38
(I) Expense	27560272	28293191	23552803	24873413	34486969
(O) Inmates	897.51	1171.16	818.61	731.55	733.33
(O) # of Disciplinary Reports	1043.48	1321.15	1089.91	1028.74	1052.83
(H1) Medical Services	6%	10%	7%	14%	21%
(H2) Adult Education	76%	72%	75%	74%	82%
(H3) Literacy Training	75%	78%	79%	69%	86%
(H4) GED Programs	84%	84%	84%	89%	92%
(H5) Special Ed Programs	30%	29%	27%	28%	34%
(H6) ESL	23%	28%	24%	31%	39%
(H7) College Courses	24%	40%	24%	36%	41%
(H8) Vocational Training	47%	61%	58%	49%	58%

(H9) Mental Health	6%	10%	11%	12%	18%
(H10) Private	27%	21%	16%	18%	15%
(H11) Security Level	56%	43%	47%	47%	48%
(H12) Employment Counseling	61%	76%	77%	77%	79%
(H13) 3 Strike Rule	60%	32%	47%	35%	39%
(H14) Gender	10%	5%	10%	11%	11%

In Table 5, the first column presents our input, output, and grouping variables (Hypotheses). The second column shows the averages for these variables among correctional facilities with an efficiency score (E) of 1. Facilities with efficiency scores less than 1 were divided into quartiles based on efficiency scores: the first quartile ranges from 0.99988 to 0.51773, the second from 0.51742 to 0.40642, the third from 0.40638 to 0.32143, and the fourth from 0.32001 to 0.14551.

In analyzing the data, we sought to identify trends that would reveal variables providing clear advantages in helping correctional facilities achieve higher efficiency. Variables associated with lower scores consistently showed trends that contributed to improved efficiency. These variables include medical services, adult education, literacy training, GED programs, ESL classes, vocational training, employment counseling, management type (private or public), and security level. The table below indicates the percentage of correctional facilities within each quartile that belong to the target group.

One notable observation from the table 5 is that higher-capacity correctional facilities are more likely to be in the efficient category or within the first quartile. In contrast, it is evident that older correctional facilities tend to be less efficient; the fourth quartile has an average facility age of 58 years, compared to 30.9 years for benchmark facilities. The fourth quartile also contains the highest number of professional staff, suggesting that staffing levels may contribute to inefficiency. Additionally, the number of disciplinary reports appears consistent across quartiles with both low and high capacity. This suggests that less efficient facilities may have a more disruptive inmate population, as they report similar numbers of incidents despite having fewer inmates.

Regarding grouping variables, some variables did not align with our model, such as medical services, adult literacy, GED programs, and vocational counseling, which showed higher representation in the lower-efficiency quartiles. However, private correctional facilities and those with minimum security levels did follow the model, with the highest percentages appearing in the most efficient quartiles.

DISCUSSION

Comparison with Past Studies

The data analysis in this study supports Hypothesis #1, confirming the statistical significance of the medical treatment variable. Correctional facilities with onsite medical services showed higher efficiency, a finding consistent with Maguire *et al.* (2023), which highlighted that onsite medical treatment reduced operational costs, primarily by preventing the spread of infectious diseases. This alignment with previous research highlights the crucial role of healthcare in enhancing efficiency within correctional facilities.

For Hypotheses #2 to #8, which focused on educational programs, the data also provided robust support. Our findings align with studies by Spelman (2009), Esperian (2010), and Stickle and Schuster (2023), all of which linked educational programs with reduced recidivism rates and operational costs. By equipping inmates with essential skills, these programs reduce reoffense rates and contribute to facility efficiency, demonstrating the value of educational initiatives within correctional settings.

Hypothesis #9 regarding mental health treatment also found strong support in the data. Facilities that offered mental health services showed statistically significant efficiency improvements, consistent with Beaudry *et al.* (2021) and Maguire *et al.* (2023), who emphasized the role of mental health resources in lowering incident rates, including suicides, within correctional environments. This suggests that mental health support not only improves inmate welfare but also enhances facility operations by reducing disruptive incidents.

Contrary to Hypothesis #10, our results revealed that private correctional facilities did not achieve greater efficiency than public ones. This finding aligns with the Prison Policy Initiative (2025), which found little evidence to support the claim that private facilities are inherently more cost-effective or efficient than public ones. This suggests that the expected cost-saving efficiencies of private facilities may not always materialize, calling for a more nuanced examination of private versus public management in correctional contexts.

The data also supports Hypothesis #11 concerning security levels, indicating that facilities with minimal security tend to be more efficient than those with higher security. Although prior studies on this specific correlation are limited, our results introduce a new perspective, suggesting that minimal-security facilities may operate more efficiently due to reduced resource demands. This finding could guide future research on the relationship between security levels and operational efficiency.

Hypothesis #12 related to employee counseling, however, was not supported by the data. Despite Spelman's (2009) findings on the cost-effectiveness of rehabilitation and counseling programs, our results did not indicate a statistically significant correlation between employee counseling and efficiency. This discrepancy may suggest that the impact of employee counseling on operational efficiency is complex and may vary depending on other factors, such as facility type or inmate demographics.

The data strongly supports Hypothesis #13 about the three-strike laws. Facilities in states with these laws exhibited higher efficiency scores, a trend similarly observed by Sutton (2013) in California. Sutton's study noted that three-strike laws might deter repeat offenses, potentially improving operational efficiency by reducing inmate turnover. However, while our study shows a correlation, policymakers should consider that this efficiency gain could stem from increased operational pressures and overcrowding, rather than from reduced recidivism alone.

Hypothesis #14 was not supported, as there was no statistically significant link between gender-specific facilities and efficiency. This finding contrasts with Wright and Cain (2018)'s study, which suggested that female facilities experience fewer violent incidents, implying potential efficiency gains. Our study's results, however, indicate that gender alone may not sufficiently influence efficiency, suggesting that other factors may drive the efficiency variations observed in gender-specific facilities.

Theoretical Implications

The theoretical contributions of this study offer significant insights into the application of efficiency modeling within correctional facilities, while also enhancing our understanding of the factors that influence operational outcomes in penal institutions.

Firstly, this study extends the application of Data Envelopment Analysis (DEA) to the correctional sector, adding to the efficiency measurement literature in non-profit and government organizations. By incorporating correctional facility-specific input and output variables, such as security levels, medical services, and educational programs, this study demonstrates how DEA can be adapted to assess efficiency within a highly regulated, resource-intensive environment. This adaptation broadens the utility of DEA as a theoretical framework for analyzing public sector efficiency, especially in settings with complex objectives that extend beyond profit maximization.

Another contribution of this study is the substantiation of the theoretical link between rehabilitative programs (such as GED programs, vocational training, and adult education) and efficiency in correctional settings. Previous studies, including those by Spelman (2009) and Esperian (2010), have suggested that educational programs reduce recidivism and related costs. By confirming these relationships with empirical data, this study strengthens the theoretical foundation that investment in rehabilitative services enhances efficiency in correctional environments. This underscores the need to consider rehabilitative outputs as essential elements in theoretical models of penal efficiency.

Additionally, this study contributes to the theoretical development of DEA by incorporating undesirable outputs, such as recidivism rates and disciplinary incidents, into efficiency analysis. Correctional facilities inherently manage these negative outcomes, which present unique challenges to traditional efficiency measurement. By including these outputs within the DEA framework, this study aligns with undesirable output DEA models, providing a more realistic model that can be applied to other social service sectors facing similar challenges. This approach extends the literature on undesirable outputs in DEA, offering a nuanced understanding of how negative factors impact facility efficiency.

The analysis of three-strike laws and their impact on facility efficiency introduces another theoretical perspective on the influence of policy on operational outcomes. While studies like Sutton (2013) have examined the effects of three-strike laws on sentencing, this study presents a novel angle by linking such laws to efficiency. This finding suggests that policies can indirectly drive facility adaptations to resource constraints, contributing to theoretical discussions on how legal and regulatory frameworks shape efficiency in correctional institutions and other policy-driven sectors.

The study also makes a theoretical contribution by analyzing efficiency across security levels. The results indicate that minimal-security facilities are more efficient than higher-security facilities, potentially due to reduced resource demands. This finding suggests that security levels should be considered a fundamental variable in theoretical models of correctional efficiency. The inclusion of security levels adds depth to theoretical discussions on efficiency in environments where security demands heavily impact resources.

Finally, this study's findings on regional variations in efficiency scores (for example, lower efficiency in New England states) contribute a theoretical basis for considering geographic and institutional factors in efficiency models. This suggests that regional factors, such as fixed costs, labor markets, and state-specific regulations, may significantly influence the efficiency of correctional facilities. The findings extend the theoretical discourse on efficiency to include geographic economic and institutional influences, providing a framework for future research on regional determinants of efficiency.

Managerial Implications

This research highlights several actionable insights for correctional facility administrators and policymakers. For example, our results confirm that educational programs, such as literacy training and GED courses, significantly enhance facility efficiency. Managers could advocate for these programs to reduce recidivism and promote productive inmate engagement, which in turn contributes to lower long-term operational costs. Educational initiatives keep inmates engaged in constructive activities, potentially reducing the likelihood of violent behavior and promoting a rehabilitative environment.

Our findings also suggest that correctional facilities in states with three-strike laws operate with higher efficiency, possibly due to operational adjustments required to accommodate larger inmate populations. While these laws may deter repeat offenses, the associated overcrowding might lead facilities to adopt cost-efficient practices. Policymakers should therefore carefully consider the long-term impacts of three-strike laws on facility operations and resource allocation, particularly given the potential for unintended consequences, such as resource strain.

Moreover, the data indicate that the least efficient facilities are concentrated in New England states, such as New Hampshire, Rhode Island, and New York. Facility managers in these states may benefit from collaborative efforts to identify common challenges and implement shared solutions. For example, higher fixed costs related to food, labor, or land in these regions may contribute to lower efficiency scores, and cooperative cost-sharing initiatives could help mitigate these regional disparities.

CONCLUSION

This study aimed to calculate the relative efficiency scores of correctional facilities by examining various grouping variables, including educational programs, security levels, and three-strike laws, using

Data Envelopment Analysis (DEA). Our findings confirmed that variables like GED classes, ESL programs, three-strike laws, special education classes, adult education, literacy training, security level, management type (private or public), vocational training, medical services, and mental health services had statistically significant impacts on efficiency scores. These results suggest that the structure and services offered within correctional facilities are key drivers of operational efficiency, with rehabilitative and educational services enhancing performance by reducing recidivism and improving inmate outcomes.

Direction for Future Studies

This research faced limitations primarily due to the dataset used, which was derived from a 2005 census conducted by the Bureau of Justice Statistics. Due to the age of the data, certain variables were either limited or missing, which restricted the scope of analysis. Future studies could benefit from more recent datasets, with greater inclusion of variables that reflect modern correctional practices, including technological advancements in surveillance, rehabilitation, and inmate management. Furthermore, since the available dataset lacked granular recidivism and cost data at the facility level, future research could aim to obtain data that allows for a direct examination of these elements.

Another limitation was the inability to isolate facility-specific factors, such as annual costs and recidivism rates. Future research could address this by seeking facility-level data rather than state-level averages, thereby improving the precision of efficiency analyses. This study included various types of correctional facilities, ranging from high-security to camp settings, which may have introduced variability in the findings. Future studies should consider categorizing facilities by type to examine efficiency differences based on security and operational demands.

Additionally, emerging studies, such as those by Cesaroni and Lamberti (2014) and Link and Reece (2021), highlight the role of technology in enhancing the efficiency of correctional facilities. Future research could investigate technological innovations, such as electronic monitoring and automated data systems, to quantify their influence on efficiency. In examining multicollinearity, future research should avoid input variables that exhibit nonsignificant correlations, such as security staff and capacity. Expanding the scope to international correctional facilities may also provide useful comparative insights, highlighting differences in efficiency between countries.

REFERENCES

Alda, E. (2022). Does Size Influence Jail Efficiency? An Analysis of Local Jails in the United States. Corrections: Policy, *Practice and Research*, *7*(2), 1–21.

Baharudin, N.A. (2022). A Review of Data Envelopment Analysis (DEA) Approach in Nonprofit Organizations. *UMK Scholar*.

Banker, R., Natarajan, R., & Zhang, D. (2019). Two-stage estimation of the impact of contextual variables in stochastic frontier production function models using data envelopment analysis. *European Journal of Operational Research*, *278*(2), 368–384.

Berkeley School of Public Policy. (2025). *Report Provides In-Depth Look at Three-Strikes Law in California*. Retrieved from https://gspp.berkeley.edu/research-and-impact/news/recent-news/report-provides-in-depth-look-at-three-strikes-law-in-california

Berglund, J., Bjursell, C., & Hugo, M. (2025). Research on education in prisons: A scoping review. *International Journal of Lifelong Education*, *44*(4), 436–449.

Beaudry, G., Yu, R., Perry, A.E., & Fazel, S. (2021). Effectiveness of psychological interventions in prison to reduce recidivism: A systematic review and meta-analysis of randomised controlled trials. *Lancet Psychiatry*, *8*(9), 759–773.

Butler, T.W., & Johnson, W.W. (1997). Efficiency evaluation of Michigan prisons using data envelopment analysis. *Criminal Justice Review*, *22*(1), 1–15.

Carey, P.D. (2018). Post-secondary correctional education program usefulness of ex-offenders' participation: Utilization-focused evaluative case study. *ProQuest*.

Cesaroni, G., & Lamberti, A. (2014). Technical efficiency and productivity analysis of the Italian prison system: A methodological comparison. *International Journal of Business Performance Management*, *15*(4), 329–350.
Cicero Institute. (2024). *Aligning profit with outcomes in private prison procurement*. Retrieved from https://ciceroinstitute.org/research/aligning-profit-with-outcomes-in-private-prison-procurement/
Connecticut Department of Correction. (2014). Annual report 2014. State of Connecticut. Retrieved from https://portal.ct.gov/DOC/Reports/Annual-Reports
Crowhurst, E., & Harwich, E. (2016). *Unlocking prison performance.* Reform. Retrieved from https://re-state.co.uk/wp-content/uploads/2018/10/Unlocking-prison-performance-web.pdf
De Sousa, M.C., Cribari-Neto, F., & Stosic, B.D. (2005). Explaining DEA technical efficiency scores in an outlier-corrected environment. *Brazilian Review of Economics*, *25*(2), 287–313.
Drago, F., Galbiati, R., & Vertova, P. (2011). Prison conditions and recidivism. *American Law and Economics Review*, *13*(1), 103–130.
Dulisse, B.C., Fitch, C.H., & Logan, M. (2020). No Silver Lining: Evaluating the Need for Consistent and Appropriate Functionality Assessments Among the Increasing and Incarcerated Elderly Population. *Criminal Justice Review*, *45*(4), 484–501.
Esperian, J.H. (2010). The effect of prison education programs on recidivism. *Journal of Correctional Education*, *61*(4), 316–334.
Garland, B., *et al.* (2014). *Corrections in the United States: Trends and Issues.* Lexington Books.
Golany, B., & Storbeck, J.E. (2019). A data envelopment analysis of the operational efficiency of bank branches. *Interfaces*, *29*(3), 1–115.
Hall, L.L. (2015). Correctional Education and Recidivism: Toward a Tool for Reduction. *Journal of Correctional Education (1974-)*, *66*(2), 4–29.
Hall, M.J.B., Liu, W.B., Simper, R., & Zhou, Z. (2013). The economic efficiency of rehabilitative management in young offender institutions in England and Wales. *Socio-Economic Planning Sciences*, *47*(1), 38–49.
Hennebel, V., Simper, R., & Verschelde, M. (2017). Is there a prison size dilemma?: An empirical analysis of output-specific economies of scale. *European Journal of Operational Research*, *262*(1), 306–321.
Henrichson, C., & Delaney, R. (2012). The Price of Prisons: What Incarceration Costs Taxpayers. *Federal Sentencing Reporter*, *25*(1), 68–80.
Hollenbeak, C.S., Schaefer, E.W., Penrod, J., Loeb, S.J., & Smith, C.A. (2015). Efficiency of health care in state correctional institutions. *Health Services Insights*, *8*, 9–15.
Jacobson, M. (2006). *Downsizing Prisons: How to Reduce Crime and End Mass Incarceration.* New York: NYU Press.
Legislative Analyst's Office. (2024). *The 2024-25 Budget: California Department of Corrections and Rehabilitation* [PDF]. California. Retrieved from https://lao.ca.gov/reports/2024/4852/CDCR-022224.pdf
Link, T.C., & Reece, B. (2021). Barriers to the Adoption of Technological Innovations in Corrections: A Review and Case Study. *International Journal of Offender Therapy and Comparative Criminology*, *65*(2–3), 262–281.
Maguire, T., Young, M., Najda, M., Jackson, H., Ryan, J., Furness, T., & McKenna, B. (2025). Developing Safewards Secure for Mental Health Prison Units Using a Nominal Group Technique. *International Journal of Mental Health Nursing*, pp. 1–16.
Nyhan, R.C. (2002). Benchmarking tools: An application to juvenile justice facility performance. *The Prison Journal*, *82*(4), 423–439.
Orrick, E., & Vieraitis, L. (2015). The Cost of Incarceration in Texas: Estimating the Benefits of Reducing the Prison Population. *American Journal of Criminal Justice*, *40*, 399–415.
Prison Policy Initiative. (2025). *Winnable criminal justice reforms in 2025*. Retrieved from https://www.prisonpolicy.org/reports/winnable2025.html

Rogge, N., Simper, R., & Verschelde, M. (2015). An analysis of managerialism and performance in English and Welsh male prisons. *European Journal of Operational Research*, *241*(1), 348–359.
Sherman, H.D., & Zhu, J. (2006). *Service productivity management: Improving service performance using data envelopment analysis (DEA).* Springer.
Smith, P.A. (2020). *Progression of restorative justice programs and their effectiveness on recidivism and being cost-efficient.* ProQuest.
Smith, T.J., & Roberts, K.M. (2023). Effectiveness of positive psychology interventions in correctional settings: Reducing self-harm and aggression. *Journal of Correctional Mental Health*, *12*(1), 45–62.
Spelman, W. (2009). Crime, cash, and limited options: Explaining the prison boom. *Criminology & Public Policy*, *10*(1), 9–53.
Steiner, B. (2009). Assessing static and dynamic influences on inmate violence levels. *Crime & Delinquency*, *55*, 134–161.
Stickle, B., & Sprick Schuster, S. (2023). Are Schools in Prison Worth It? The Effects and Economic Returns of Prison Education. *American Journal of Criminal Justice*, *48*(6), 1263–1294.
Sutton, J.R. (2013). Symbol and substance: Effects of California's three strikes law on felony sentencing. *Law & Society Review*, *47*(1), 37–72.
Tobón, S. (2022). Do better prisons reduce recidivism? Evidence from a prison construction program. *Review of Economics and Statistics*, *104*(6), 1256–1272.
Towns, Z., Ricciardelli, R., & Spencer, D.C. (2024). "I feel like it should be but I know it's really not": Exploring physical fitness priorities at the correctional training program in Canadian federal corrections. *International Journal of Qualitative Studies on Health and Well-Being*, *19*(1).
Vitner, G., Rozenes, S., & Spraggett, S. (2006). Using data envelopment analysis to compare project efficiency in a multi-project environment. *International Journal of Project Management*, *24*(4), 323–329.
Wright, E.M., & Cain, C.M. (2018). Women in prison. In *The Oxford handbook of prisons and imprisonment* (pp. 163–188). Oxford University Press.
Wu, A., & Huang, C.-J. (2003). Efficiency performance and the drivers of efficiency: The test of correctional institutions. *Taiwan Accounting Review*, *3*(2), 113–139.