Operational Assessment of Nursing Homes at Times of Pandemic: An Integrated DEA and Machine Learning Approach

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Abstract

Assessing the performance of nursing homes during pandemics such as COVID-19 is critically important, particularly in light of an aging global population and the heightened need for long-term care. This urgency has led to a heightened global emphasis on optimizing nursing home resources. To address this objective, we developed a hybrid method that integrates Data Envelopment Analysis (DEA) with Machine Learning (ML) techniques to improve and predict the performance of these facilities. We applied this innovative approach to over 500 nursing homes across Pennsylvania. Given the complex regulatory and funding environments, with significant variations across regions, we performed a comparative efficiency analysis using DEA across three Pennsylvania regions: West, East, and Central. Once we identified the sources of inefficiency, we suggested actionable solutions to improve these facilities. We further utilized ML techniques to predict efficiency of nursing homes. Our results showed that the number of citations, complaints, COVID-19 cases, and COVID-19 related deaths as critical factors affecting nursing home efficiency. Comprehensive approaches to address these factors include refining staff training programs, adopting regular feedback mechanisms, enhancing regulatory compliance, strengthening infection control practices, and managing resources effectively. These measures are vital for improving the quality of care and operational efficiency in nursing homes.

Keywords*:* Nursing home performance; COVID-19; DEA; Predictive analytics; Machine learning.

1 Introduction

Effective management of hospitals and nursing homes is of utmost importance in the current era of rising healthcare costs and challenges related to the shortages of skilled workers and adequate facilities to address pandemics like COVID-19 (American Hospital Association (AHA) 2023). The National Council of State Boards of Nursing (NCSBN) (2023) reveals that 100,000 nurses left the workforce during the pandemic and by 2027, almost one-fifth of 4.5 million total registered nurses, intend to leave the workforce, threatening the national health care system at large if solutions are not enacted. For nursing homes specifically, a study reported by Health Affairs indicates that nearly half of U.S. nursing homes had to rely on agency staff by 2022, significantly increasing costs and often correlating with lower quality ratings. This chronic staffing issue continues to pose risks to patient safety and care quality, urging a reevaluation of workforce strategies post-pandemic (Fierce Healthcare 2024). Additionally, the Pandemic Oversight (2023) committee reported that during the pandemic, 94% of surveyed nursing homes experienced a nursing shortage, highlighting the severity of staffing issues in long-term care facilities during health crises. Furthermore, nursing homes represent a substantial and costly component of the overall healthcare sector (Shimshak et al. 2009). According to the Penn Wharton Budget Model (2022), Medicaid's spending on long-term care services, including nursing homes, is projected to increase from $130 billion in 2020 to $179 billion by 2030.

Besides cost considerations, long-term care and nursing homes are becoming crucial as people are living longer and the proportion of older people in society is increasing, thus pushing the need for Long Term Care (Adamek and Balaswamy 2016; World Health Organization (WHO) 1995). The nursing home population has been significantly impacted by the COVID-19 pandemic. As of February 2021, there were approximately 625,000 confirmed cases of COVID-19 reported among residents of U.S. nursing homes, constituting approximately 23% of the total COVID-19 cases in the United States (Williams et al. 2021). During this timeframe, nursing home residents accounted for 26% of the reported COVID-19 related deaths (Centers for Disease Control and Prevention (CDC) 2021a, b). More than 90% of nursing homes documented at least one confirmed case of COVID-19 among their residents, and approximately

77% of these facilities reported at least one COVID-19-related death among their residents. Furthermore, there were significant variations in COVID-19 infection and death rates among different nursing homes (Centers for Medicare and Medicaid Services (CMS) 2021). Given the ongoing high incidence of COVID-19 and the potential for new variants or other infectious diseases to lead to future outbreaks, it is imperative to prioritize the evaluation of nursing home performance within the healthcare system (Rasi et al. 2020; Rahimi et al. 2014; Shimshak et al. 2009). Additionally, understanding the key factors that impact the performance of nursing homes and identifying strategies to enhance the efficiency of less effective facilities becomes of utmost importance.

In the majority of countries, over 50% of national healthcare resources go to waste due to inefficient utilization and allocation of limited resources (Rasi et al. 2020). Healthcare providers have encountered numerous challenges, particularly resource and personnel shortages, in the face of pandemics. COVID-19, in particular, has presented a significant threat to healthcare systems due to unprecedented demands that surpass the system's capacity in terms of medical supplies, ICU availability, technology, beds, ventilators, as well as healthcare professionals (Satomi et al. 2020). Consequently, enhancing the quality of healthcare services and delivering superior care to patients necessitates the evaluation of healthcare organizations' performance to address these issues by minimizing inefficiencies (Shimshak et al. 2009). Furthermore, the adoption of an effective performance assessment model would empower healthcare providers to identify areas of inefficiency, devise strategies for improvement, and subsequently enhance service quality, leading to more satisfied customers and patients.

Studying nursing home performance during the COVID-19 pandemic is crucial for several compelling reasons. Firstly, nursing homes house some of the most vulnerable populations to COVID-19, including the elderly and those with underlying health conditions. Assessing performance helps identify best practices and areas needing improvement in infection control, resident care, and staff response. These insights are invaluable as they guide enhancements in health protocols and preventative measures, ensuring better protection for these vulnerable groups. Moreover, the evaluation provides valuable insights into how these facilities can better prepare for future public health crises, enhancing their operational readiness and resilience. Additionally, understanding how nursing homes respond to such health crises allows for the development of robust strategies that ensure rapid and effective responses, which are crucial in mitigating the impact of such events. The significance of this research is underscored by the intertwined issues of severe workforce shortages highlighted by the American Hospital Association (AHA) (2023) and the National Council of State Boards of Nursing (NCSBN) (2023), and the direct impacts of these shortages on care quality and operational efficiency. Furthermore, the COVID-19 pandemic has exacerbated these challenges, significantly affecting nursing homes with high rates of infections and mortality among residents, as documented by the CDC (2021a, 2021b) and CMS (2021). This research is not merely an academic exercise but reflects our ethical and social responsibilities to provide competent and compassionate care to the elderly and other vulnerable groups. By highlighting the gaps and needs in elder care, this study prompts necessary societal and policy reforms aimed at improving the quality of life for these individuals. This thorough approach makes the research a vital base for creating policies and strategic plans, building a healthcare system that supports dignity and respect for everyone.

This study concentrates on evaluating the performance of nursing homes in the state of Pennsylvania (PA) and predicting their efficiency. Notably, it has been pointed out that 70% of COVID-19 deaths in PA are among nursing home residents (Proose and Woodall 2020). This underscores the critical need to assess the performance of nursing homes in PA with the aim of improving resource allocation, service quality, patient satisfaction, and cost-effectiveness. While this research is focused on Pennsylvania, its findings can be extended to other states using a similar comprehensive dataset used in this study. Conducting analyses on a state or even regional level within states is justified because nursing homes are subject to a complex array of state-specific regulatory and funding frameworks. These differences can be substantial, as noted by sources like the National Center for Assisted Living (https://www.ahcancal.org/Assisted-Living/), Kaiser Family Foundation (https://www.kff.org/), and Centers for Medicare & Medicaid Services (https://www.cms.gov/), which provide insights into these variations across states.

The study focuses on three main research objectives:

1. *Assessment and Improvement of Nursing Home Performance:* The primary objective is to assess and enhance the performance of nursing homes in Pennsylvania. Data Envelopment Analysis (DEA) was employed to categorize nursing homes as efficient or inefficient based on their inputs and outputs. Solutions were proposed to improve the performance of inefficient nursing homes by adjusting these factors.
2. *Predicting the Efficiency of New Nursing Homes:* The study aimed to predict the efficiency of new nursing homes. This was achieved by integrating the DEA optimization model with Machine Learning techniques. The efficiency scores obtained from DEA analysis were used to train Machine Learning algorithms, such as Artificial Neural Networks, Decision Trees, Support Vector Machines, and Random Forests, to predict the efficiency of new nursing homes and provide recommendations for improving their performance.
3. *Identifying Significant Variables:* The study also sought to identify which variables played a more significant role in predicting nursing home efficiency. Sensitivity analysis was employed to determine the most critical variables. Information fusion technique was used to combine the results from various Machine Learning models, providing a consolidated assessment of the variables' impact on nursing home efficiency and their relative importance.

The study is organized as follows: Section 2 presents a literature review and also clarifies the contribution of this research. The research methodology with the needed details is explicated in Section 3 and the main results are discussed in Section 4 by using evidence-based hands-on experiments. Section 5 concludes this paper with some lessons learned and possible future research directions.

2 Literature Review

The COVID-19 pandemic has profoundly affected the nursing home population because older people have been affected more than younger ones. Across the OECD countries, 93% of the COVID-19 deaths are among people older than 60 (Organisation for Economic Co-operation and Development (OECD) 2021). COVID-19 has highlighted the vulnerability of nursing home residents, who have disproportionately suffered effects of the pandemic. They are at higher risk of severe disease and mortality from COVID-19 due to their age and comorbidities. In addition, nursing homes' communal living environment increases the risk of the spread of COVID-19, particularly for nursing homes that lack adequate infection prevention and control measures to prevent transmission (CMS 2021).

In light of the ongoing prevalence of COVID-19 and the potential emergence of new variants or other contagious diseases capable of triggering future outbreaks, it is crucial to comprehend the connection between nursing home characteristics, particularly those within their control, and the incidence of COVID-19. Several studies have explored the link between COVID-19 infections and/or mortality rates and nursing home quality (Abrams et al. 2020; Figueroa et al. 2020; He et al. 2020; Li et al. 2020; Bowblis and Applebaum 2020) as well as nurse staffing levels (Li et al. 2020; Gorges and Konetzka 2020; Harrington et al. 2020). However, these studies produced mixed findings, partly due to their early execution in the pandemic, limiting their applicability to different states and varying time periods with distinct COVID-19 infection rates. Moreover, the majority of existing literature has primarily focused on COVID-19 incidence or mortality rates as the primary outcomes of interest. In contrast, there has been a notable absence of attention devoted to evaluating the overall performance of nursing homes and enhancing their performance, encompassing all factors, including those specific to nursing homes and those related to COVID-19. The lack of a consistent understanding of factors associated with COVID-19 outbreaks has hindered the development of effective responses to mitigate the effects of COVID-19. William et al. (2021) employed regression analysis to explore the relationship between the quality of care in nursing homes and COVID-19 incidence, mortality, and enduring impact. However, they solely considered the quality rating of nursing homes as a performance criterion, neglecting other factors that influence nursing home performance. To the best of our knowledge, no studies have specifically addressed the evaluation of nursing home performance. In our research, we utilized the Data Envelopment Analysis (DEA) optimization technique, which takes into account multiple inputs and outputs, to assess the performance of each nursing home and determine their relative efficiencies.

Several researchers have focused on efficiencies and optimization of healthcare operations by using techniques such as DEA. See (Darabi et al. 2021; Onen and Sayin 2018; Samut and Cafri 2015; Chen et al. 2019; Nistor et al. 2017; Afonso et al. 2023; Singh et al. 2023) for different examples of using DEA to analyze and improve the efficiencies of hospitals in different countries with different GDPs and in different time periods. Although several studies have used DEA, few focus on evaluating the performance of nursing homes. Dulal (2018) discusses the association between five-star quality ratings and technical efficiency in nursing homes using a two-stage DEA analysis. Veloso et al. (2018) aim to evaluate the economic efficiency of nursing homes and the determinants influencing their efficiency in 2012 and 2013 using DEA. Additionally, Phillips et al. (2007) evaluate nursing home performance indicators by examining the impact of facilities on changes in residents' Activities of Daily Living (ADL), using data from Medicare- or Medicaid-certified nursing homes, highlighting the importance of ADL in understanding an elderly person's abilities. The study explores the extent to which facility performance contributes to changes in ADL, a key measure of nursing home performance.

There are also studies analyzing healthcare performance by using DEA with a concentration on the effects of the COVID-19 pandemic. Kamel and Mousa (2020) assessed the performance of hospitals during the COVID-19 pandemic. They found that the number of nurses and the number of beds are the most significant variables affecting the efficiency of the hospitals. Mourad et al. (2021) assessed the performance of healthcare systems of the countries by using DEA that considers six variables including conducted COVID-19 tests, the number of affected cases, number of recovered cases, number of death cases, number of hospital beds, and medical practitioners. Rays and Lemqeddem (2021) also performed the same analysis on the primary healthcare institutions in Morocco during COVID-19 and showed that the main reason for the inefficiency of the healthcare institutions is the lack of management control. Nepomuceno et al. (2020) determined the required number of health service units during COVID-19 by using DEA. These researchers have contributed a great deal to our understanding of the healthcare systems in general and how they can be made more efficient by using the DEA method even in pandemics. Different from the previous studies, there are also some studies that assess the sustainability and resilience of healthcare supply chains against COVID-19 by using DEA (Azadi et al. 2023). To the best of our knowledge, there is no study that analyzes the performance of the nursing homes during COVID-19. The only related work is by Létourneau et al. (2022), which offered a systematic literature review to identify factors influencing the performance of long-term care facilities, including nursing homes, during the COVID-19 pandemic. This study adopted a multidimensional framework for performance evaluation that considered the aspects like accessibility and quality of services, optimization of resources, and quality of care, with a particular emphasis on infection prevention and control.

In the efficiency analysis of hospitals and other healthcare institutions, DEA is commonly used to assess operational efficiency across multiple departments or services, which typically have complex and multifaceted operational outputs. However, in the case of nursing homes, DEA is primarily used to evaluate the efficiency of care delivery and resource utilization specific to long-term care settings, with a focus on measuring the quality of care and patient satisfaction as outputs.

More recently, Machine Learning methods have also been widely used in the healthcare sector. As a subset of artificial intelligence, machine learning (ML) is applied to healthcare problems to extract meaning from large sets of data, identify patterns, and make decisions. Examples span machine learning methods for heart disease identification by using Support Vector Machine, Logistic Regression, Artificial Neural Network (ANN), K-nearest Neighbor, Naive Bayes, and Decision Tree (Li et al. 2020); prediction of diabetics disease by using Naive Bayes, Support Vector Machine (SVM), Decision Tree, Logistic Regression, and Random Forest (Sarwar et al. 2018); and the prediction on the clinical outcomes in patients having Ebola Virus Disease (Colubri et al. 2016). In the context of nursing homes, Lee et al. (2021) concentrated on identifying risk factors associated with pressure ulcers in residents, utilizing various machine learning methods like random forest and support vector machines to effectively predict these factors. Machine learning (ML) techniques in the healthcare sector are often used for clinical prediction tasks, such as diagnosing diseases or predicting patient outcomes from a wide range of clinical data. In contrast, in nursing homes, ML techniques are used to monitor and prevent adverse events, such as falls or pressure ulcers, utilizing more limited datasets than those available in hospital settings.

Several other studies have applied Machine Learning (ML) techniques to investigate COVID-19 as well. Parbat (2020) utilized Support Vector Regression to estimate the number of COVID-19-related deaths, while Yadav et al. (2020) and Khanday et al. (2020) made predictions regarding the virus's spread across different regions. Yadav et al. (2020) also delved into analyzing the transmission rate of the virus. Furthermore, some researchers have employed various ML models to forecast the future number of COVID-19 positive cases, as seen in the works of Rustam et al. (2020) and Batista et al. (2021). Ardabili et al. (2020) adopted multiple ML methods for predicting COVID-19 outbreaks and demonstrated that ML approaches are more effective in modeling the COVID-19 pandemic compared to traditional forecasting methods. Smith et al. (2020) utilized a sophisticated simulation model to understand and manage COVID-19 outbreaks. The model used dynamic data to simulate virus transmission and evaluate different surveillance strategies to effectively detect and manage outbreaks, helping to improve response strategies in nursing homes during the pandemic.

As indicated in the above literature review, although many studies used DEA to assess the performance of the healthcare systems and ML algorithms for the prediction, to the best of our knowledge, no study integrates all these disparate but interrelated developments into a powerful solution approach that could assess, predict and improve the performance of nursing homes against pandemics at a massive scale. Because nursing homes constitute a large and costly part of the overall health care industry, and the high percentage of COVID-19 deaths are among older people, the performance assessment of the nursing homes and the improvement of the inefficient nursing homes have the highest priority. There are still gaps in the existing literature that require further research to enhance our understanding of different impact factors and their collective influence on the performance of the nursing homes. Additional studies are needed to address these gaps and gain a more comprehensive understanding of the complex relationship between various factors and their combined effects on nursing home efficiency. A significant gap in evaluating nursing home performance during COVID-19 is the lack of real-time, comprehensive data that accurately reflect the dynamic nature of the pandemic. This includes detailed information on infection rates, staffing levels, and the implementation and effectiveness of infection control measures. Additionally, there's a need for standardized metrics to compare performance across facilities and to gauge the impact of specific interventions on resident outcomes. Addressing these gaps is crucial for improving care quality and preparedness in future health crises.

The main contributions of this study are as follows:

- First, a comprehensive data was used to evaluate the nursing home performance during COVID-19, including COVID related data such as number of cases, infection rates, number of deaths as well as facility related data such as staffing levels, quality rates, number of citations and penalties, their capacity, etc.
- Second, the DEA model was used to evaluate the nursing home performance and identify the efficient and inefficient nursing homes, make a benchmark between them, and provide insights into how to improve inefficient ones. Our analysis provides a benchmark between the three regions of PA and allows policymakers to see their inefficient sides to improve them and be more efficient.
- Third, integration of the DEA model with Machine Learning Techniques renders predictive models that predict the efficiency of the new nursing homes and determine the most significant variables which have the highest impact on the nursing home performance.
- Fourth, utilizing several machine learning techniques including ANN, SVM, Random Forest, and Decision Trees captures complex non-linear relationships between the efficiency of the nursing homes and the factors affecting this efficiency.
- Fifth, developing an information fusion-based sensitivity analysis that combines the results of several ML techniques while recognizing the prioritized significance of factors associated with nursing homes since they are related to the efficiency of the nursing homes. So, instead of trusting only a single ML model, the collaboration of different prediction methods as input for sensitivity analysis helped us to come up with the important factors which are positioned according to their significance to the predicted outcome.

Thus, this study tries to fill many gaps in the existing literature and could contribute to improving the extant practice and knowledge base. This new knowledge may provide policymakers with new and useful insights into how providers are performing in terms of nursing home services and what needs to be done urgently.

3 Research Methodology

In this study, a hybrid method that integrates an optimization model with Machine Learning models was used. The framework of the proposed methodology consisting of five stages is shown in Fig. 1. The first stage is data identification and collection which includes three steps involving the identification of the variables, determination of inputs and outputs of the model, and finally data collection and preparation for the analysis. In stage 2, Data Envelopment Analysis (DEA) which is a linear programming-based optimization model was developed, and the efficiency of the nursing homes was determined. We also obtained what potential improvements are required to make inefficient units more efficient. The results of the optimization models were input to Stage 3 which integrates the optimization model with Machine Learning Models to predict the efficiency of the nursing homes. In this stage, four ML techniques were employed, their performances were compared concerning some performance criteria and the relative importance of the variables was determined for each ML model.

In stage 4, information fusion-based sensitivity analysis was used to show collectively what variable has the highest impact on the prediction of efficiency of nursing homes by combining the relative importance of the variables of each ML model obtained in the previous stage. Finally, in stage 5, the results were analyzed and discussed with the expert who is working at University of Pittsburgh Medical Center (UPMC) Pinnacle Post-Acute Care Service to verify.

In this study, we evaluated the nursing homes in PA. There are 6 regions identified by the Pennsylvania Department of Health shown in Fig. 2. The number of counties and the nursing homes for each PA region is also given in Table 1.

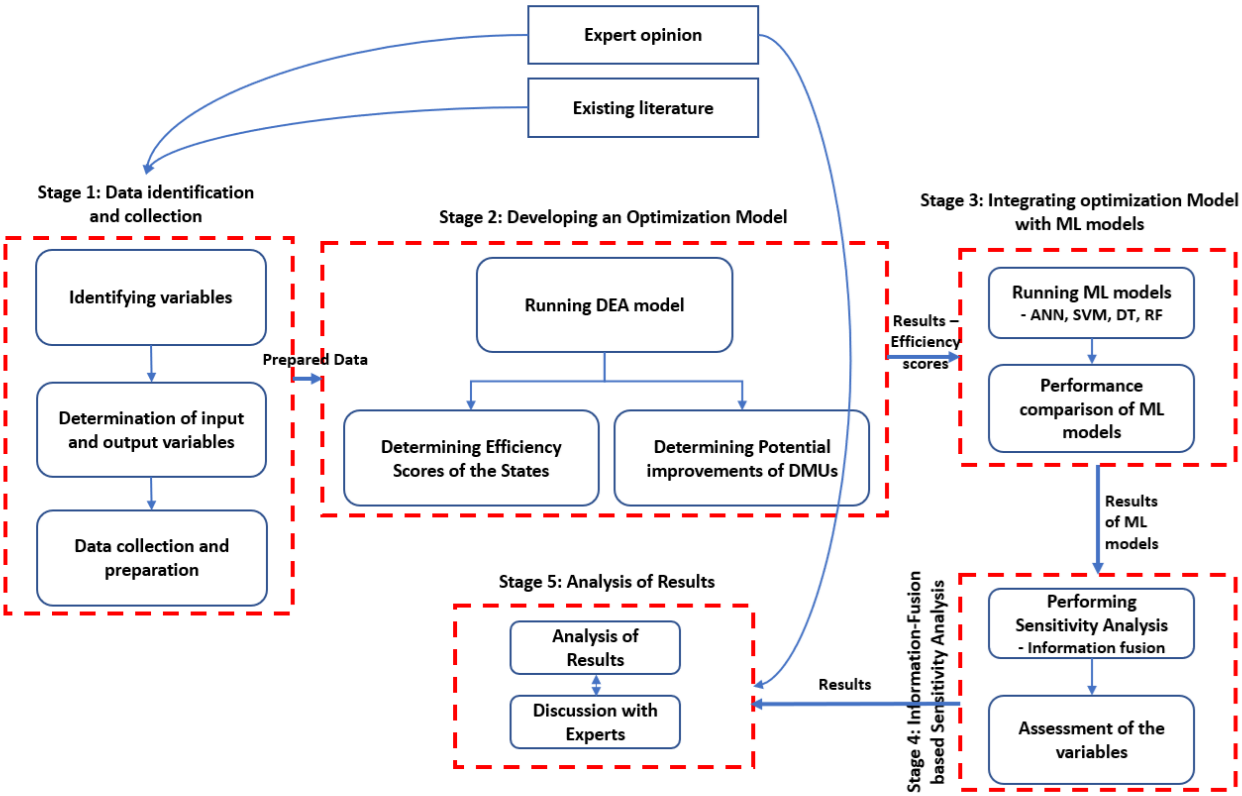

Fig. 1 Framework of the proposed model

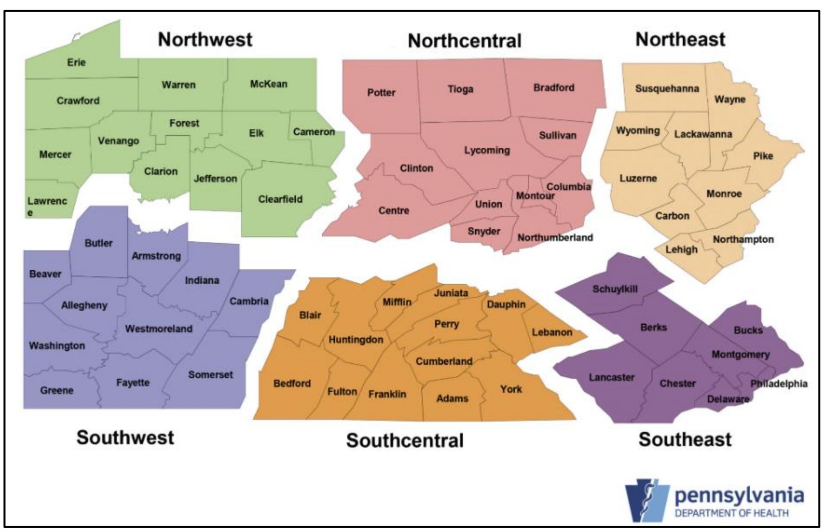

Fig. 2 Regional map of Pennsylvania

This framework was adjusted for each big region and we compared the regions in terms of the nursing home efficiencies and the required potential improvements of the variables and then discussed what variables show differences among the regions. In the following subsections, the details are given about each stage.

Table 1 Number of nursing homes in each PA region

Region	Number of Counties	Number of Nursing Homes	Big region	Total number of nursing homes
Southcentral	13	92	Central	140
Northcentral	12	48		
Southwest	11	142	West	217
Northwest	13	75		
Southeast	8	248	East	336
Northeast	10	88		
Total	**67**	**693**		**693**

3.1 Stage 1: Data identification and collection

The effectiveness of the units assessed within the DEA model is contingent upon the chosen variables, both in terms of inputs and outputs (Wang et al. 2016). To ascertain these variables, we conducted a comprehensive review of existing literature and consulted with experts. From this process, we identified a total of 23 variables, categorizing 15 of them as inputs and 8 as outputs in our proposed model. The data were collected through three websites: https://data.cms.gov/, https://www.medicare.gov/, and https://www.health.pa.gov/. The definition of the variables is given in Table 2. Different from the existing studies, we included a very comprehensive dataset which consists of COVID-19 related data such as number of cases and number of deaths as well as nursing home related data such as quality ratings, capacity of the facility, number of citations and penalties, and number of tests administered to residents and staff. Considering the number of COVID-19 cases, the number of COVID-19 deaths (McMichael et al. 2020; He et al. 2020; Dora et al. 2020), and the number of tests administered to both residents and staff (Grabowski and Mor 2020) are crucial for evaluating the performance of nursing homes during the COVID-19 pandemic. We also had discussions with the expert at UPMC especially regarding cost, quality and funding and regulatory changes.

While *cost* is an important factor in the management and operation of nursing homes, using it as a primary metric for performance evaluation without considering the broader context of quality of care, resident needs, and long-term outcomes may not provide a holistic view of efficiency. The primary objective of nursing homes is to provide high-quality, long-term care and improve residents' quality of life. Unlike acute care settings where cost-effectiveness can be more directly related to specific medical outcomes (e.g., surgery success rates), in nursing homes, the correlation between cost and quality of care is more nuanced. High costs do not necessarily mean poor efficiency if they result in significantly improved resident satisfaction and quality of life. In addition, nursing homes operate within complex regulatory and funding environments, with significant variations across regions. In some cases, funding levels are not directly related to the performance of the nursing home but are determined by regulatory frameworks and government policies. So, this disconnection between performance and funding can make cost a less relevant or logical metric for performance evaluation in these contexts (Grabowski 2020; Musumeci and Chidambaram 2020; Harrington et al. 2017).

Quality is fundamentally the cornerstone of nursing home performance, serving as the primary metric through which care, safety, and resident satisfaction are gauged. In the context of nursing homes, quality transcends basic compliance with health standards; it encompasses the holistic well-being and satisfaction of residents. Studies have shown that higher quality ratings are associated with better health outcomes, including lower rates of hospitalization and improved rehabilitation outcomes (Castle and Ferguson 2010). In this study, we used “short stay quality rating” that shows the average rating of the residents' short-stay care experience, “long stay quality rating” that shows the average rating of the residents' long-stay care experience, and “overall rating” which is based on a nursing home's performance on 3 sources: health inspections, staffing, and quality of resident care measures. The overall rating offers a holistic assessment of a nursing home's performance. This approach aligns well with healthcare quality standards that prioritize personalized, resident-centered outcomes. By focusing on these varied yet interconnected aspects of quality, the DEA model comprehensively evaluates the multifaceted nature of nursing home performance, ensuring a balanced and thorough appraisal of each facility's capacity to deliver high-quality, resident-centered care.

The Centers for Medicare & Medicaid Services (CMS) utilize these ratings to provide transparent and accessible information to consumers about the quality of care in nursing homes. This includes a detailed methodology for calculating each of these ratings based on health inspections, staffing, and quality measures (Centers for Medicare & Medicaid Services 2021). Harrington et al. (2012) also indicates the direct correlation between staffing ratios, skills mix, and the quality of resident care underscores the relevance of including these factors in the overall rating. Additionally, analyses suggest that public reporting of these ratings drives improvements in care quality, as facilities strive to improve their publicly reported outcomes (Werner et al. 2009).

Although *funding and regularity changes* variables play also a substantial role in determining the operational capabilities and care quality of nursing facilities, there are several challenges and considerations associated with including these factors. One of the main hurdles in including funding and regulatory changes in performance evaluations is the availability and consistency of data. Funding levels can vary widely depending on the source (e.g., public vs. private funding), and capturing accurate and consistent data across different facilities and regions can be challenging. Similarly, regulatory changes are often jurisdiction-specific and can change over time, making it difficult to standardize this information for comparative analysis. Moreover, regulatory changes might have different impacts based on how each nursing home implements these changes, which can vary widely even within the same regulatory framework. Additionally, including these factors requires a thoughtful research design that can isolate the effects of funding and regulatory changes from other variables. This often necessitates a longitudinal study design or sophisticated econometric models that can handle multiple confounding factors simultaneously (Grabowski and Gruber 2007; Mor et al. 2010). Therefore, we didn’t consider funding and regularity changes in this analysis.

Table 2 Definition of the variables

Variable Names	Input/Output	Variable Definition
Total Resident COVID-19 Deaths Per 1,000 Residents	Input	For every 1000 residents how many died from COVID-19
Residents Total All Deaths	Input	The total number of residents who died from all causes
Total Resident Confirmed COVID-19 Cases Per 1,000 Residents	Input	For every 1000 residents how many were confirmed to have from COVID-19
Staff Total Confirmed COVID-19 Cases	Input	The total number of staff that were confirmed to have COVID-19
Staff Total COVID-19 Deaths	Input	The total number of staff that died from COVID-19
Penalties $$	Input	The dollar amount the provider has been charged for penalties.
Number of Penalties	Input	A count of the individual penalties that a nursing home has received
% of SSR re-hospitalized	Input	Percentage of short-stay residents who were re-hospitalized after admission to a nursing home
% of SSR with Outpatient Emergency Visit	Input	Percentage of short-stay residents who have had an outpatient emergency department visit
% of SSR receiving medication for the first time	Input	Percentage of short-stay residents who got antipsychotic medication for the first time
No. of hospitalization per 1000 LSR days	Input	Number of hospitalizations per 1,000 long-stay resident days
No. of Outpatient emergency visits per 1000 LSR days	Input	Number of outpatient emergency department visits per 1,000 long-stay resident days
% of LSR receiving medication	Input	Percentage of long-stay residents who got an antipsychotic medication
No. of Complaints in the last 3 years	Input	Number of complaints in the last 3-year period
No. of Citations in last 3 years.	Input	Number of citations in the last 3-year period
No. of Tests on Residents	Output	The total number of COVID-19 tests administered to residents
No. of Tests on Staff	Output	The total number of COVID-19 tests administered to staff
Overall Rating	Output	The overall rating is based on a nursing home's performance on 3 sources: health inspections, staffing, and quality of resident care measures on a scale of 1-5.
Short Stay QR	Output	The average rating on a scale of 1-5 of the residents' short-stay care experience
Long stay QR	Output	The average rating on a scale of 1-5 of the residents' long-stay care experience
Staff rating	Output	The staffing rating is based on the Registered Nurse (RN) hours per resident per day; and the total nurse staffing hours per resident per day and is rated on a scale of 1 – 5
Health IR	Output	The health inspection star rating is based on each nursing home's current health inspection, two prior inspections, and the findings from the most recent 3 years of complaint inspections and infection control inspections on a scale of 1 – 5.
Usage Rate	Output	The percentage of the used total bed capacity on average by the provider

3.1.1 Stage 1: Data preparation

DEA analysis requires some characteristics to interpret the results accurately. Thus data preparation is very important before beginning the analysis. We preprocessed the data under the three subheadings to make it ready for the DEA analysis since some requirements should be met before running the DEA model.

Evaluating the size of the nursing homes

The number of inputs and outputs, as well as the number of Decision Making Units (DMUs), are very important in DEA while providing good discrimination between efficient and inefficient units. There are many insights about the determination of the number of DMUs. While Golany and Roll (1989) recommended the number of units should be at least twice the total number of inputs and outputs, Bowlin (1998) established that it should be three times the total number of input and output variables. Dyson et al. (2001) also suggested that the suitable number of DMUs is at least two times the multiplication of the number of inputs and outputs. In addition, Boussofiane et al. (1991) mentioned that the highest performance is achieved when the number of DMUs is at least the multiplication of the number of inputs and the number of outputs. We followed the rule of thumb that Boussofiane et al. (1991) suggested. Because we have 15 inputs and 8 outputs, only the rule suggested by Golany and Roll (1989) is met for each region of PA as seen in Table 1 whereas the other rules require more number of nursing homes. To satisfy the needs of other rules, we narrowed our analysis to the 3 main big regions including Central (Southcentral and Northcentral), West (Southwest and Northwest), and East (Southeast and Northeast) of PA which has 140, 217, and 336 nursing homes, respectively (see Table 1). After eliminating the missing variables, we had 105 nursing homes in the Central region, 136 nursing homes in the West region, and 259 nursing homes in the East region.

Eliminating correlated variables

We then checked if the variables are correlated to get more accurate results and save computational time. The correlated variables may provide a slightly different answer. So, the results may depend on the accepted correlation level (Sarkis 2007). We used Spearman's rank correlation to assess the relationship between both continuous and categorical variables because the categorical variables used in our case study are ordinal. Thus, we examined the correlation of the input and output variables for each region and observed no significant correlations among the variables. This is why we included all variables in the DEA analysis.

Adjusting imbalanced data

Finally, we made sure that the data have no imbalance. When the variables are not of similar magnitude, the large variable dominates the computation of DEA and produces unreliable DEA results (Sueyoshi and Goto 2013). To have the data at the same or similar magnitude, we normalized the data set by simply dividing each observation by the average of variable values (Sarkis 2007).

3.2 Stage 2: Developing the optimization model

Data Envelopment Analysis (DEA) was used to assess the performance of the nursing homes in PA in this study. DEA is very powerful for efficiency calculations and is also quite popular in performance evaluation of the decision-making units. DEA is a linear programming model that provides an objective assessment of similar organizational units' efficiency (also called decision-making unit (DMU)) by considering multiple input and output variables and converting them into a single performance measurement for each DMU (Charnes et al. 1978). It does not require any prior weight for inputs and outputs, and they are measured independently without being converted into a single unit (Huang and McLaughlin 1989). DEA decides on the best weights for each variable for a particular DMU to maximize its relative efficiency (Ivlev et al. 2014; Ramezani-Tarkhorani and Shirdel 2023). DEA is also a non-parametric technique that uses linear programming to estimate the frontier functions. It searches for the optimal points with the lowest input for the given output and connects these points to find the efficiency frontier. The efficiency frontier shows the best relationship between outputs and inputs (Kocisova et al. 2018). For each DMU, the efficiency score is calculated relatively based on the other DMUs. The relative efficiency of a DMU takes a value between 0 and 1. A value of 1 indicates that the mentioned DMU is relatively efficient and values less than 1 indicate that the DMU is relatively inefficient. So, we have a chance to make better use of resources and make them efficient.

However, the goal of DEA is not only to determine the efficiency scores of the DMUs. It also allows how to improve inefficient units by finding the target values of each input and output. It calculates them by determining the practical benchmarks of the inefficient units which are called peers or reference sets that are pure efficient (Kocisova et al. 2018). So, by using DEA, we determined the efficient and inefficient nursing homes, the reference sets of each inefficient nursing home, and the target values for each input and output of the nursing homes that need to be improved to make them efficient.

The fundamental DEA model, known as the CCR model, derives its name from its creators: Charnes, Cooper, and Rhodes (Charnes et al. 1978). DEA models can be categorized based on their treatment of returns to scale. Charnes et al. (1978) initially assumed that the Decision-Making Units (DMUs) operate under the condition of constant returns to scale (CRS). Subsequently, Banker et al. (1984) introduced the BCC model, which allows for variable returns to scale (VRS) efficiency assessment by incorporating weight constraints. This extension enables the decomposition of efficiency into technical and scale efficiency components. DEA models can also be classified as input-oriented or output-oriented. The input-oriented model aims to minimize inputs while maintaining constant output levels, whereas the output-oriented model seeks to maximize outputs while keeping input levels constant (Ji and Lee 2010).

DEA is a well-established method in efficiency and performance evaluation across various sectors, including healthcare, due to its ability to handle multiple input and output variables without requiring a priori weighting. Notably, Emrouznejad and Yang (2018) provide a comprehensive review of DEA's application in healthcare settings, highlighting its utility in assessing the efficiency of hospitals and other health facilities. Additionally, Jacobs et al. (2006) discuss the methodological frameworks of DEA in healthcare, offering insights into its capabilities and benefits specifically in this sector. Although DEA is a powerful tool for efficiency measurement, it comes with certain limitations and potential biases that are important to understand when interpreting its results, including sensitivity to outliers, the risk of overestimating efficiency in the presence of noise in data, and its deterministic nature that does not account for statistical noise (Cooper et al. 2011; Banker et al. 2004). Additionally, DEA does not provide a direct way to handle quality variations beyond the defined inputs and outputs, which can be critical in healthcare settings. Coelli et al. (2005) and Thanassoulis (2001) discuss both the strengths and weaknesses of DEA in various operational and service settings, including healthcare.

In our study, we have adopted the input-oriented DEA model because it aligns with the objectives of our Decision-Making Units (nursing homes). This model strives to minimize input levels while holding output levels constant, thereby maximizing efficiency. This choice is consistent with the healthcare context and well-suited for our analysis (Nahra et al. 2009). Nursing homes, as part of the healthcare sector, operate under the principle of maximizing resident care and satisfaction, which makes the input-oriented approach highly relevant (Tran et a. 2019; Wu 2023). Moreover, for nursing homes, this involves providing the highest quality of care with the fewest resources. In our case, the outputs of the model include the short-stay and long-stay quality ratings, as well as the overall quality rating. This approach is particularly pertinent when control over outputs is limited due to external factors, such as fixed care standards or resident needs, making it more feasible to focus on optimizing inputs. In addition, the input-oriented CCR model allows for the identification of best-performing DMUs as benchmarks for others. In the context of nursing homes, this can be instrumental in highlighting practices that lead to efficient use of resources while maintaining high-quality care, providing clear targets for others to strive for (Tran et a. 2019; Wu 2023).

The general dual form of the input-oriented envelopment CCR model is as follows:

$$Min\ E_k = \alpha - \varepsilon \sum_{i=1}^{m} S_i^- - \varepsilon \sum_{r=1}^{p} S_r^+ \tag{1}$$

$$s.t.$$

$$\sum_{j=1}^{n} X_{ij}\lambda_j + S_{ik}^- - \alpha X_{ik} = 0 \tag{2}$$

$$\sum_{j=1}^{n} X_{rj}\lambda_j + S_{rk}^+ = Y_{rk} \tag{3}$$

$$S_{ik}^-, S_{rk}^+, \lambda_j \geq 0 \quad \forall i = 1,2,\dots,m; r = 1,2,\dots,p; j = 1,2,\dots,n \tag{4}$$

where E_k is the efficiency score of *k*th DMU, X_{ij} is the value of input *i* for the DMU *j*, Y_{rk} is the value of output *r* for the DMU *k*, α is the shrinking coefficient, λ_j is the density value for the DMU *j* and is the raw weight assigned to the peer units of an inefficient DMU *j*. λ_j dual variables come from the theory of linear programming and they are also known as shadow prices related to the constraints that limit the efficiency of each DMU to be less than 1. We also know that when a constraint is binding, a shadow price will be positive and when the constraint is non-binding the shadow price will be zero. Hence, a binding constraint implies that the corresponding unit is efficient and has an efficiency score of 1, and has a positive dual variable λ. So, the positive values for λ_j dual variables identify the peer group for any inefficient unit. In addition, in the above model S_i^- denotes the slack value of input *i* for the DMU *k*, S_{rk}^+ is the surplus-value of output *r* for the DMU *k*, *p* is the number of outputs, *m* is the number of inputs and *n* is the number of DMUs.

3.3 Stage 3: Integrating the optimization model with ML models

In this stage, we integrated the results of the DEA optimization model with Machine Learning models. It is highly beneficial to predict the efficiency of a nursing home and then take proactive actions to make it more efficient. Because we have unlabeled data that do not have any indicator that shows the efficiency of the nursing homes, we first ran the DEA model and obtained the efficiency scores of the nursing homes. Then we utilized these results as the output variable of the ML models.

3.3.1 Machine Learning (ML) models

Several ML models were used to predict the efficiency of a nursing home including Artificial Neural Network (ANN), Random Forest (RF), Decision Trees (DT), and Support Vector Machines (SVM). Existing literature clearly shows that these ML techniques achieve high accuracy (e.g. Uddin et al. 2019; Wang et al. 2020). Drawing from this robust empirical evidence, we selected these models due to their proven effectiveness and reliability in healthcare analytics settings. Moreover, the primary goal of employing multiple machine learning models in our study was not only to leverage their known high accuracy but also to conduct a comparative analysis of their performance in our specific dataset. This approach allows us to assess and identify which model provides the best performance in terms of accuracy, generalizability, and computational efficiency when applied to the efficiency prediction of nursing homes. All variables used in the DEA model were considered as the inputs and the efficiency scores obtained by the DEA model were considered as the output variable of the ML models. These ML models used in this study were described as follows.

Artificial Neural Network

Artificial Neural Networks draw inspiration from biological processes and are adept at modeling intricate non-linear functions. These networks consist of interconnected neurons, which are typically organized into layers, including input, hidden, and output layers. Depending on the complexity of the problem at hand, there can be multiple hidden layers nestled between the input and output layers. To emulate the signal processing and activation observed in biological systems, artificial neurons employ mathematical functions like sigmoid activation functions.

In this study, we harnessed the power of a multi-layer perceptron (MLP) coupled with a back-propagation supervised learning algorithm—a widely recognized and popular choice within the realm of neural network architecture. MLPs excel in handling both prediction and classification tasks. As highlighted by Delen (2010), MLPs possess the remarkable capacity to learn highly intricate non-linear functions with a remarkable level of accuracy, provided they are configured with the appropriate size and structure.

We employed 10-fold cross-validation to train our neural network model, limiting the training to 100 iterations to mitigate overfitting because the model started to converge to a minimum in the loss function after 80 iterations. In neural networks, tuning parameters such as the number of hidden neurons (size) and the regularization term (decay) significantly influence the model's ability to generalize beyond the training data. The decay parameter helps prevent overfitting by penalizing larger weights within the model. To identify the best hyperparameters, we evaluated several combinations of size and decay through cross-validation. Our approach was guided by a balance between model complexity and the risk of overfitting. The tuning process determined that the best settings were a size of 5 and a decay of 0.1. Having 5 neurons allows the network to model more complex relationships than networks with fewer neurons, yet remains simple enough to avoid overfitting, which is crucial given the complexity of the task. A decay factor of 0.1 is moderate, ensuring that the model weights do not become excessively large, which would make the model overly sensitive to noise in the training data. These decisions were continuously refined through an iterative process using cross-validation, which provided a robust framework for evaluating the impact of different configurations on the model's performance. Additionally, we used a logistic (sigmoid) activation function for the output neuron, appropriate for the classification task in this study. The logistic function's smooth gradient helps during backpropagation by ensuring that small changes in weights lead to consistent changes in output probabilities, aiding the convergence during training.

Decision Trees

Decision trees are one of the most popular and powerful classification methods because of their explainable characteristics. They are also used for prediction problems. Several decision tree algorithms, including C4.5 (Quinlan 1993), C5 (Delen 2010), and Classification and Regression Trees (CART) (Breiman et al. 1984; Delen et al. 2012), are available. These algorithms generate relatively clear and interpretable model structures compared to opaque structures like Artificial Neural Networks (ANN) and Support Vector Machines (SVM). In this particular study, we employed CART to assess the effectiveness of nursing homes.

In the training of our decision tree model, we utilized 10-fold cross-validation to ensure consistent model performance across different data partitions. A critical tuning parameter in this process is the complexity parameter (cp), which we carefully adjusted to control tree complexity and prevent overfitting. After exploring various cp values, cp=0.188 was selected as optimal, indicating a preference for a simpler model to enhance generalizability and reduce the risk of overfitting identified at lower cp values. This cp setting ensures that the tree only splits when there is at least an 18.8% decrease in impurity, leading to a tree with fewer, more significant branches.

Additionally, we employed the minsplit and minbucket tuning parameters to further refine the tree's structure. Minsplit was set to 20, meaning a node must have at least 20 observations before considering a split, thus limiting excessive tree growth and complexity. Minbucket was set to about one-third of minsplit, at 7 observations, defining the minimum size of our terminal nodes (leaves). This setup supports making stable and reliable predictions by ensuring that each leaf has a sufficient number of observations to underpin its predictions, balancing detail and overfitting avoidance effectively.

Random Forest

Random Forest is an ensemble algorithm based on decision trees. It consists of many decision trees each one of which produces a response when presented with a set of predictor values. Since it is not sensitive to noise in the data and is subject to overfitting, it provides excellent performance. Instead of using a single decision tree, it creates several decision trees on the sample data and merges their output to enhance the performance of a model. While merging the results of decision trees, it uses Bagging or Bootstrap aggregation which helps to reduce the variance of the model and improve the classification performance (Basri and Arif 2021). In Random Forest, each decision tree is trained on the random subsets of data samples and sampling is done with replacement. In addition, it chooses random features at each split and reduces correlation.

In the training of our random forest model, we utilized 10-fold cross-validation and focused on optimizing two key hyperparameters: the number of trees (ntree) and the number of variables sampled at each split (mtry). These parameters critically influence the model's accuracy and computational efficiency. Increasing the number of trees generally improves the model's stability and accuracy by reducing prediction variance through averaging multiple trees. However, the benefits diminish after a certain point, increasing computational costs without substantial performance gains. The mtry value, on the other hand, affects the diversity and correlation among the trees in the forest. A lower mtry increases diversity and reduces inter-tree correlation, which can enhance the model's generalizability but might weaken individual trees. Conversely, a higher mtry makes trees stronger but more similar, increasing their correlation. After experimentation, we found that setting ntree to 500 and mtry to 2 provided the best performance for our dataset, ensuring robustness and stability while maintaining computational efficiency. This configuration leverages a large ensemble of trees to average out errors effectively and uses a limited number of variables per split to minimize tree correlation, thereby enhancing the model's ability to generalize to new data.

Support Vector Machines

Support Vector Machines is one of the most popular supervised learning methods. It learns from the training data to produce input-output functions. They are used for both classification and regression problems and belong to a family of generalized linear models that achieves a classification or regression decision based on the linear combination of features' values. Kernel functions are utilized for classification to transform the given data which shows highly complex non-linear relationships to a high dimensional space that enables inputs linearly separable. To effectively distinguish the classes in training data, maximum-margin hyperplanes are constructed. On each side of the hyperplane, two hyperplanes are constructed parallel to each other that separate the data via maximizing the distance between these parallel hyperplanes. It is accepted that the distance between the parallel hyperplanes determines the generalization error that can be interpreted as the larger margins produce better generalization errors for the classification (Cristianini and Taylor 2000).

In this study, we evaluated the model using both linear and non-linear kernels, specifically the radial basis function (RBF). We aimed to enhance model performance by tuning the cost (C) and sigma parameters, where the cost parameter manages the trade-off between minimizing training errors and reducing model complexity to improve generalization. Sigma, critical for the RBF kernel, determines the extent of influence a single training example has, with smaller values indicating a broader impact. After adjusting the cost parameter C across a spectrum from 0.01 to 100 for both kernels, and sigma from 0.01 to 100 for the RBF kernel, the best results were achieved with an RBF kernel set at sigma = 0.1 and C = 0.01. The combination of a moderate **sigma** and a low **C** suggests that the model prioritizes generalization over perfectly fitting the training data. Additionally, during the testing phase, the model with these parameters most effectively balanced accuracy and generalization. This is an important outcome, as it suggests the model is well-tuned to handle data beyond the scope of what it was trained on.

3.3.2 k-fold cross-validation

k-fold cross-validation was used to validate the accuracy of the predictive models because it minimizes the bias of sampling for training and testing data. The whole data is randomly split into *k* mutually exclusive folds which are equal in size. The model is trained on *k*-1 data folds and tested on the remaining data fold. So, the model is tested *k* times by using the test sets and the overall *k*-fold cross-validation is calculated by taking the average of the *k* individual performances as given in Eq. (5) (Oztekin 2018):

$$CV = \frac{1}{k}\sum_{i=1}^{k} PM_i \tag{5}$$

where *CV* represents the cross-validation, *k* shows the number of mutually exclusive subsets, and *PM* is the performance measure used in the analysis. In this study, we chose *k* as 10 which is commonly used in the literature and provides a good balance between the classification performance and the required time to run the predictive models (Oztekin 2018; Kohavi 1995).

In this study, different subsets for training and testing were used to ensure that the model does not just memorize the training data but generalizes well over new, unseen data. We experimented the training dataset size between 70% and 90% for each machine learning technique with various tuning parameters. The results of our experiments indicate that using 80% of the data for training and 20% for testing yielded the highest accuracy for all ML techniques.

3.3.3 Performance measures

Four performance metrics were used to compare the performances of the predictive models including Accuracy, Sensitivity, Specificity, and AUC which are given below:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{7}$$

$$Specificity = \frac{TN}{TN+FP} \tag{8}$$

where TP and TN represent the true positives and true negatives whereas FP and FN represent the false positives and false negatives, respectively. In our case, *Accuracy* shows the proportion of correctly classified nursing homes, *Sensitivity* shows the ability of the model to correctly identify efficient nursing homes and *Specificity* shows the ability of the model to correctly identify inefficient nursing homes.

AUC metric was also used in this study which shows the area under the curve of all possible combinations of sensitivity and (1 – specificity). Hence, it gives a more accurate measure of the models' performance (Simsek et al. 2020).

3.4 Stage 4: Information fusion-based sensitivity analysis

3.4.1 Sensitivity Analysis

This study has a specific goal of identifying the key variables that play a pivotal role in predicting the efficiency of nursing homes. To achieve this objective, we employed sensitivity analysis as a valuable tool to assess how these variables impact the output variable, which, in this context, represents the efficiency score of nursing homes. This approach also afforded us the opportunity to gauge the relative significance of each variable by systematically removing them from the model, one at a time. This is represented by Eq. (9):

$$S_i = \frac{V(x_i)}{V(y)} = \frac{V(E(y|x_i))}{V(y)} \tag{9}$$

where *y* denotes the output variable (efficiency scores of the nursing homes), S_i denotes the contribution or variable importance of variable x_i, which is also calculated as a normalized sensitivity measure, $V(y)$ denotes the variation in the output variable, and $V(E(y|x_i))$ refers to the variance of the expected value of all variables except variable x_i.

3.4.2 Information fusion

Information fusion is used to combine the information of multiple sources to increase the accuracy of the information. Cang and Yu (2014) mentioned that information fusion increases the quality of the model and Clemen (1989) supported that information fusion decreases the uncertainties and biases of a single model by combining the information of multiple models and hence provides a better prediction estimate. But the existing literature (Oztekin 2018; Simsek et al. 2020) also mentioned that there is no single or best way to aggregate the information in predictive models and the decision can be given by the trial-and-error way.

While there are limited direct examples of information fusion in nursing homes, the technique has been applied effectively within broader healthcare contexts. For instance, Simsek et al. (2020) conducted a study on breast cancer survival, crucial for clinicians to predict outcomes and devise effective treatment strategies. In this study, information fusion was utilized to pinpoint the significance of various variables across different models and timeframes. Similarly, Dag et al. (2017) developed predictive models for 1-, 5-, and 9-year patient graft survival post-heart transplant, using four advanced classification algorithms. They employed information fusion to integrate insights from these models, enhancing the overall understanding of each variable's impact on survival outcomes. Furthermore, Dag et al. (2016) utilized a Bayesian Belief Network (BBN) to elucidate interactions among predictors and the conditional probabilities of survival, based on specific donor-recipient characteristics in heart transplants. This information fusion approach was adopted from Delen et al. (2007) since it has provided robust performance in preliminary analyses and its comprehensibility to medical professionals.

In the context of this study, we employed several Machine Learning (ML) models, each yielding diverse results regarding the significance of various variables. Consequently, we opted for an information fusion-based sensitivity analysis approach, which enables us to consolidate information derived from these diverse ML models into a single combined value. This approach aids in pinpointing which variables exert the most substantial influence on nursing home efficiency and their respective rankings.

A typical prediction model can be denoted as Eq. (10):

$$\hat{y} = g(x_1, x_2, \ldots, x_n) \tag{10}$$

where x_i denotes the input variables, $\hat{y}$ denotes the output variable predicted and $g(.)$ refers to the function of a prediction model. A fusion model combines the information of multiple prediction models and the fused output variable $\hat{y}_{fused}$ can be written as seen in Eq. (11):

$$\hat{y}_{fused} = \gamma(g_1(X), g_2(X), \ldots, g_m(X)) \tag{11}$$

where γ denotes the operator that combines m predictive models and X denotes the vector of input variables. Then if we assume $\gamma(.)$ as a linear function, Eq. (11) can be written by Eq. (12):

$$\hat{y}_{fused} = \sum_{i=1}^{m} \omega_i g_i(X) \quad \text{where } \sum_{i=1}^{m} \omega_i = 1 \tag{12}$$

where ω_i denotes the weight assigned for each predictive model which is obtained from the accuracy of the models. If a predictive model has higher accuracy, it is assigned higher weights. So, there are many ways to combine the information of many models. By using information fusion, instead of relying on a single model we use different information from multiple models and reduce the uncertainties and the errors contributed to a single model and thus increase the accuracy of final data.

4 Results and Discussion

We present the results in two main categories: First is the DEA optimization results which provide the efficiency scores of the nursing homes and second is the predictive modeling results which provide a prediction model and identify the variables which are significant in the efficiency prediction of the nursing homes.

4.1 DEA optimization model results

In this section, we provide the performance evaluation results for each PA region using DEA. We also present the results obtained for all nursing homes in PA. These results include a comparison of efficiency among nursing homes in each region and identify the inputs that we need to improve to make the inefficient nursing homes full efficient. We then discuss the reasons for the inefficiencies in the nursing homes and propose potential solutions to improve their efficiency.

4.1.1 Comparison of the efficiency of the nursing homes

We conducted regional analysis to determine the efficient and inefficient nursing homes in each region. This assessment was based on a set of 15 input variables and 8 output variables, which were carefully identified through a combination of expert opinions and insights from existing literature. Fig. 3 provides the comparison of the regions in terms of their efficient and inefficient nursing homes.

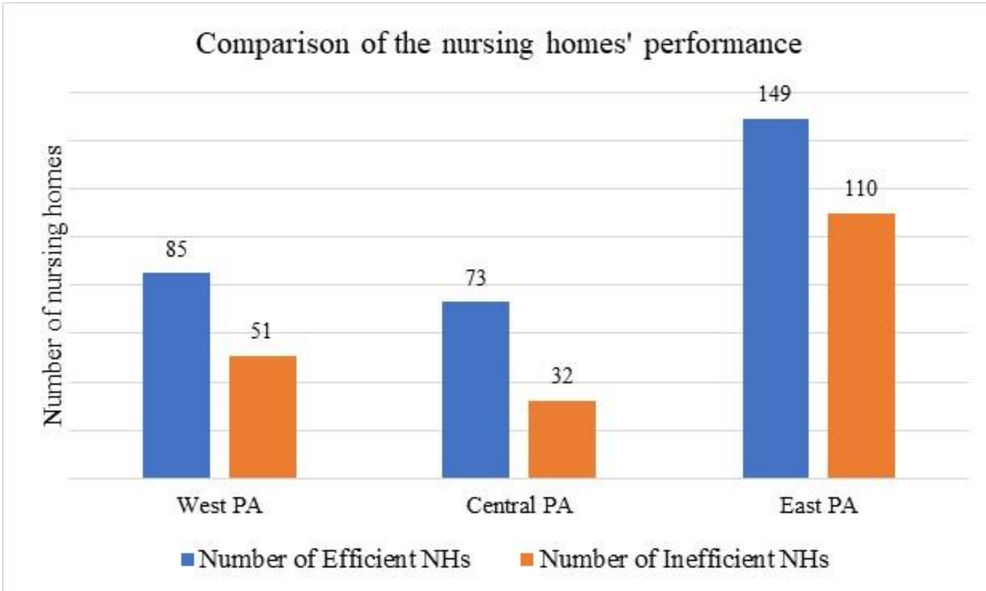

Fig. 3 Comparison of the nursing homes' performance

Our findings revealed that among 136 nursing homes in West PA, 85 achieved full efficiency scores of 100%, indicating optimal performance. Meanwhile, 51 nursing homes showed varying levels of inefficiency, meaning their efficiency was less than 100% and signifying a need for improvement to attain full efficiency. Moreover, in Central PA, 73 nursing homes demonstrated full efficiency, whereas 32 were inefficient. Among 259 nursing homes in East PA, 149 achieved full efficiency and 110 were inefficient.

Beyond merely identifying the efficient and inefficient nursing homes, our secondary objective is to offer guidance on how to enhance the performance of the underperforming facilities. The Data Envelopment Analysis (DEA) model enabled us to identify the reference units or peers for the inefficient facilities, which are considered 100% efficient for comparison purposes. Hence, we also assessed the impact of each peer on the efficiency of the inefficient unit. Fig. 4 illustrates the frequency of selected top peers that have been employed as a reference in assessing the efficiency of underperforming (inefficient) units.

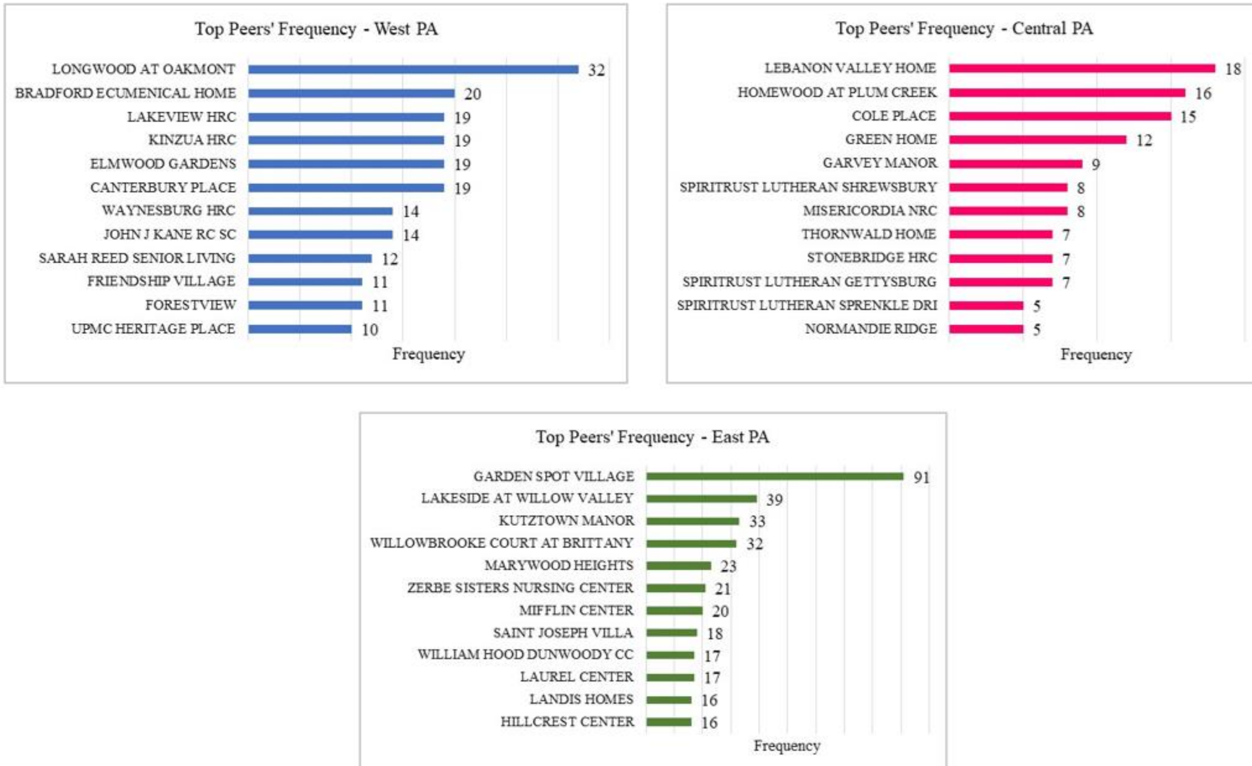

Fig. 4. Top Peers' frequency for each region

For instance, Fig. 4 highlights that the nursing home 'Longwood at Oakmont' in West PA stands out with the highest frequency, appearing as a reference in the assessment of 32 inefficient nursing homes in West PA. This underscores its role as an exemplary model of high performance. Consequently, 'Longwood at Oakmont' can be recognized as the *global leader* among nursing homes in the West PA region, offering a valuable illustration of best practices for inefficient units to emulate and investigate in terms of resource allocation and management. Moreover, nursing homes such as 'Bradford Ecumenical Home,' 'Lakeview HRC,' 'Kinzua HRC,' 'Elmwood Gardens,' and 'Canterbury Place' also exhibit relatively higher frequencies among the other full efficient nursing homes. This suggests that their resources should be closely examined to identify areas where inefficient nursing homes may be lacking and where improvements can be made.

4.1.2 Reasons of the inefficiency of the nursing homes

The most important question while analyzing the performance of the nursing homes is what causes inefficiency and how we can improve the efficiency of the inefficient nursing homes. DEA provides how to improve inefficient units by finding the target values of each input and output by using the peers of the inefficient units. Fig. 5 shows how much we should improve the inputs (decreasing the level of inputs) to make the inefficient units full efficient.

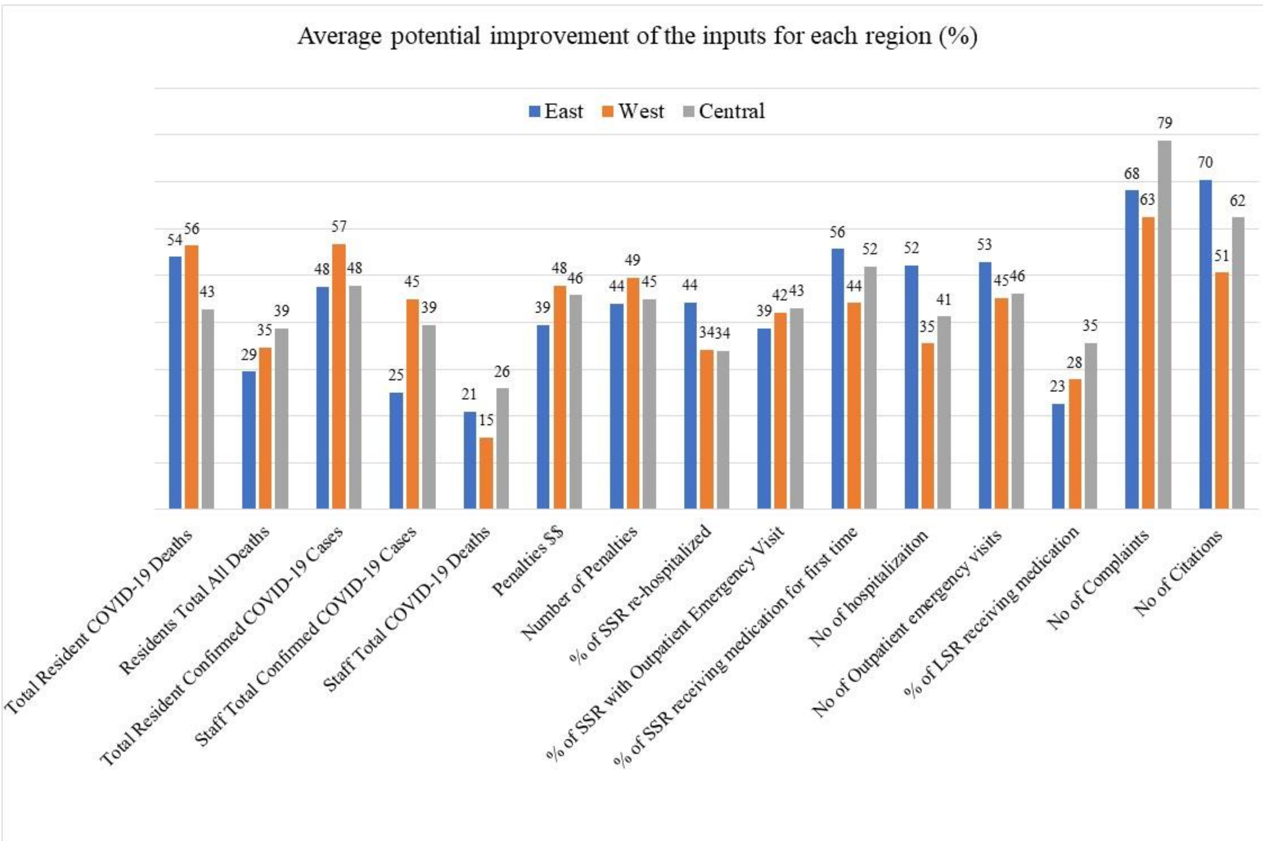

Fig. 5 Average potential improvement of the inputs for each region

Fig.5 illustrates that, across all regions, the inputs requiring the most significant improvements to enhance the efficiency of inefficient nursing homes are the Number of Complaints and Number of Citations. Additionally, it is evident from the results that nursing home efficiency is notably influenced by factors such as Total Resident COVID-19 Deaths and Total Resident Confirmed COVID-19 Cases, particularly during the pandemic. Furthermore, % of SSR Receiving Medication for the first time and the

Number of Outpatient Emergency Visits are subsequent variables that demand heightened attention and improvements compared to other factors.

From this analysis, it's clearly seen that East PA consistently shows the highest potential for improvement across most metrics, indicating significant issues in managing COVID-19 and related healthcare services. East PA, especially around Philadelphia, is highly urbanized and densely populated. Due to high population density and urbanization, East PA might have seen significant challenges in managing COVID-19 spread within nursing homes, leading to higher potential improvement percentages in resident and staff COVID-19 cases and deaths. Urban centers often face rapid transmission, which can overwhelm local healthcare systems despite better access to resources. Moreover, the volume of cases and the pressure on services likely contributed to higher numbers of complaints and regulatory penalties, indicating areas needing drastic enhancements in management and care standards.

Central PA generally shows moderate improvement needs but is particularly concerned with penalties and the number of penalties. Central PA tends to be more rural or semi-urban, with lower population densities. Rural areas might have less frequent but more severe outbreaks due to delayed responses and limited healthcare staffing. With fewer resources and possibly slower emergency responses compared to urban areas, Central PA shows notable deficiencies in handling COVID-19, reflected in higher numbers for penalties and inefficiencies.

West PA shows a somewhat lower potential for improvement compared to East but still significant, particularly in areas related to COVID-19 deaths and cases among residents and staff. West PA, with cities like Pittsburgh, combines urban settings with vast rural areas. This mix can result in varied impacts on nursing homes, where urban areas might see rapid spread similar to East PA, but rural areas might struggle with resource allocation.

A high number of complaints and citations typically reflect broader issues related to the quality of care provided. This can be due to inadequate staffing levels, where there are too few staff members to adequately meet the needs of the residents. Additionally, staff may lack sufficient training or skills, which can lead to substandard care practices, increased incidents of neglect, or abuse. Moreover, operational inefficiencies such as poor management practices, ineffective use of resources, or inadequate emergency preparedness can also lead to higher citations and complaints. These inefficiencies can exacerbate during a crisis, like a pandemic, highlighting the need for robust management systems. Furthermore, compliance with continually evolving healthcare regulations is another critical factor. Facilities that struggle to keep up with or implement new regulations effectively can face increased citations, impacting their overall efficiency scores.

The prominence of COVID-19 related variables also indicates issues with infection control practices within facilities. This can stem from inadequate protocols for disease prevention and control, insufficient personal protective equipment, or poor adherence to existing protocols. These deficiencies indicate not only lapses in routine hygiene and safety protocols but also in emergency preparedness and response strategies. During the pandemic, these factors have been particularly critical in determining the spread and impact of the virus in closed environments like nursing homes.

The health status and complexity of residents' medical conditions can also influence the efficiency of care. Facilities with a higher proportion of residents having severe or multiple health conditions may experience more challenges in managing care effectively, thus impacting their performance metrics. Additionally, inefficient allocation of financial and human resources can also lead to poorer outcomes. This includes failure to invest in quality improvement initiatives, staff development, or modern healthcare technologies that can improve care delivery and disease management.

Addressing these issues comprehensively involves enhancing staffing protocols, improving regulatory compliance, fortifying infection control measures, and ensuring efficient resource management, which are essential steps towards optimizing care quality and operational efficiency in nursing homes.

4.1.3 Results for all nursing homes in PA state

While our primary focus was to evaluate the regional performance of nursing homes, we expanded our analysis to encompass all nursing homes within the state of Pennsylvania. This broader assessment allowed us to make comparisons with regional results and discern whether significant differences exist among the variables requiring improvement. This comprehensive evaluation provides valuable insights for nursing home administrators, highlighting the areas where they should concentrate their efforts to attain pure efficiency.

Out of the 500 nursing homes in Pennsylvania, 286 were identified as efficient, while the remainder exhibited varying degrees of inefficiency across a spectrum of efficiency scores.

Fig. 6 provides a breakdown of the input variables that require improvement for the inefficient nursing homes. The inputs demanding the most substantial improvements are the Number of Citations, Number of Complaints, and % of SSR receiving medication for the first time, aligning with the findings observed in regional analysis. Furthermore, Total Resident COVID-19 Deaths, Total Resident Confirmed COVID-19 Cases, and Number of Outpatient Emergency Visits are the subsequent variables that warrant increased attention and enhancements, mirroring the trends observed in other regions.

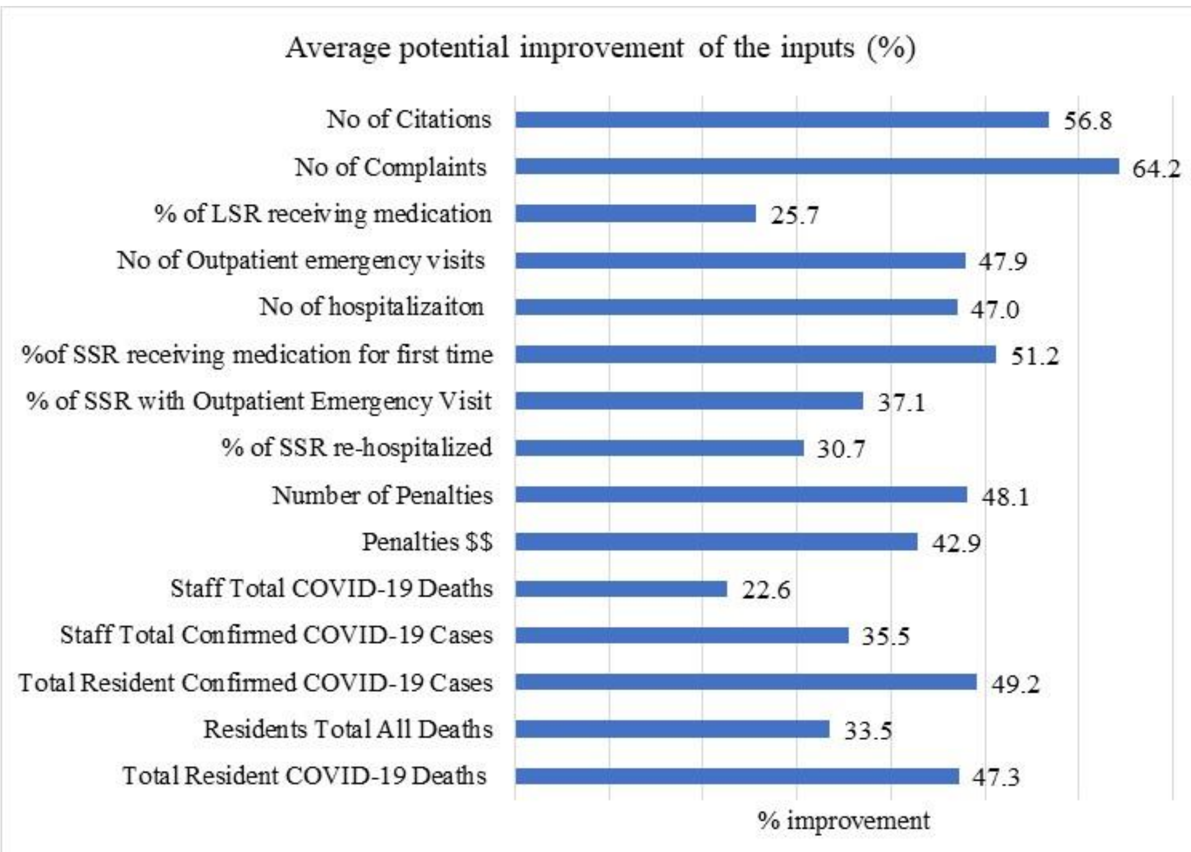

Fig. 6 Average potential improvement of the inputs for all inefficient nursing homes in PA state

4.1.3 Solutions on improving the efficiency of the nursing homes

The significant roles played by 'Number of Citations' and 'Number of Complaints' in the DEA analysis highlight critical areas where nursing homes can focus their improvement efforts to enhance overall efficiency. Addressing these issues requires targeted strategies such as improving staff training, revising internal policies, and enhancing resident care protocols to reduce citations and complaints effectively.

Furthermore, COVID-19 related variables such as 'Total Resident COVID-19 Deaths' and 'Total Resident Confirmed Cases' also indicate the areas that require more substantial improvements compared to other inputs to enhance the efficiency of inefficient nursing homes. The importance of these COVID-19 related variables underscores the urgent need for robust infection control measures, continuous staff training in infectious disease management, and improved communication channels for timely response to outbreaks. These actions are not only vital for enhancing immediate healthcare outcomes but also for strengthening the resilience of nursing homes against future health crises.

To better guide healthcare managers and policy makers, we propose a framework for integrating these insights into practical decision-making. This includes establishing a continuous monitoring system to track the effectiveness of implemented changes, engaging in periodic training and development sessions for staff, and setting up collaborative platforms for sharing best practices among facilities. Additionally, policy recommendations could focus on revising funding allocations to support the necessary improvements in staff training and infrastructure, thereby directly linking our research findings to policy actions.

4.2 Hybrid model results: Integration of DEA with ML Models

In this section, we integrated the results from the Data Envelopment Analysis (DEA) model with various Machine Learning (ML) techniques, including Artificial Neural Networks (ANN), Random Forest, Decision Trees, and Support Vector Machines. The efficiency score obtained from the DEA model, representing nursing home efficiency, served as the output variable for the ML models. Additionally, all the inputs and outputs from the DEA model were utilized as input variables for the ML models.

The primary objective of this predictive modeling was twofold: first, to predict whether a nursing home can be classified as efficient or inefficient, and second, to discern which variables wield the most significant influence in predicting nursing home efficiency. To accomplish this, we employed a 10-fold cross-validation technique for each ML model. Consequently, we conducted a total of 160 model runs (4 ML models x (3 regions + the entire state of PA = 4) x 10 folds) throughout the course of this study. In the subsequent subsection, we present and compare the results for each region, with a focus on identifying significant variables.

4.2.1 Comparison of the ML models for the three PA regions

Four different ML models were employed to classify the efficiency of the nursing homes. The performance results of each ML model are given in Table 6. As seen in Table 6, Random Forest provided the highest performance in terms of all performance metrics used for the analysis.

Table 3 Performance results of ML models for all PA regions

Region	Model	Sensitivity	Specificity	Accuracy	AUC
West PA	**Support Vector Machines**	0.51	0.86	0.73	0.86
	Neural Network	0.68	0.76	0.73	0.81
	Decision Tree	0.58	0.80	0.72	0.67
	Random Forest	**0.73**	**0.87**	**0.85**	**0.91**
East PA	**Support Vector Machines**	0.63	0.83	0.75	0.84
	Neural Network	**0.76**	0.77	0.77	0.80
	Decision Tree	0.60	0.84	0.74	0.75
	Random Forest	0.73	**0.93**	**0.84**	**0.91**
Central PA	**Support Vector Machines**	0.30	0.91	0.76	0.86
	Neural Network	0.65	0.75	0.73	0.80
	Decision Tree	0.40	0.84	0.73	0.75
	Random Forest	**0.45**	**0.97**	**0.84**	**0.91**

We used information fusion to assess the variable importance and get more reliable results instead of relying on only a single model. After sensitivity analysis was done for each ML model to get the individual variable importance, information fusion was performed to aggregate the results and find a single fused importance value for each variable. Fig. 7 presents the comparative findings in terms of predicting nursing home efficiency for each region.

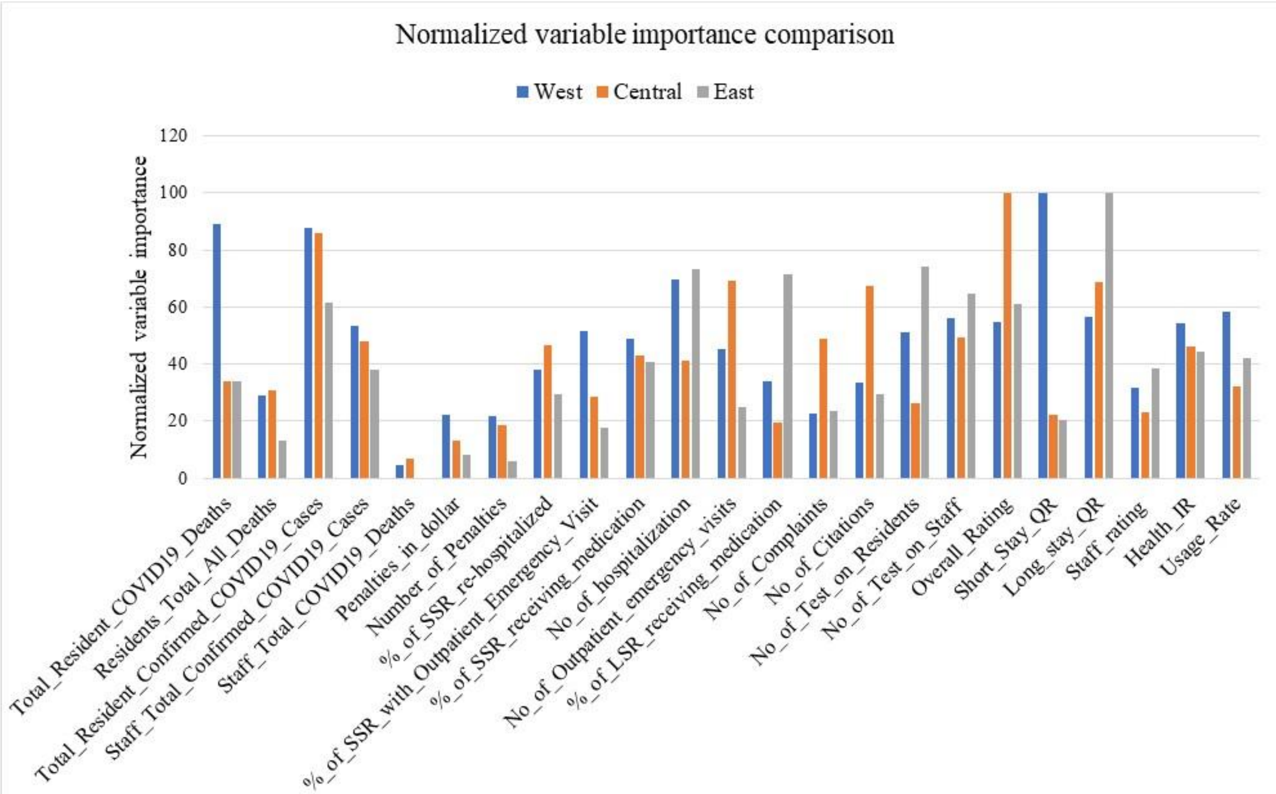

Fig. 7 Comparison of the PA regions in terms of variable importance in the prediction

As depicted in Fig. 7, quality ratings emerged as highly influential factors in predicting efficiency across all regions. Notably, the variable 'Quality Rating,' encompassing both short stay and long stay quality ratings, as well as staff ratings, held significant importance in predicting the efficiency of nursing homes in Central PA. In West PA, 'Short Stay QR' proved to be the most pivotal variable, while in East PA, 'Long Stay QR' had the most pronounced impact on efficiency prediction. Quality related variables reflect resident experiences and outcomes, which are central to evaluating facility performance. High quality ratings often correlate with better resident satisfaction and overall operational efficiency. Thus, their significance in predicting efficiency is not only expected but crucial for any comprehensive analysis.

Furthermore, variables related to COVID-19 demonstrated a substantial influence on efficiency prediction. 'Total Resident COVID-19 Confirmed Cases' exhibited significant importance in the prediction models for nursing homes in both West and Central PA, while 'COVID-19 Resident Deaths' had a greater impact in the West region. Additionally, the 'Number of Tests on Residents' had a higher influence on efficiency prediction in the Central region. COVID-19 related variables also reflect how well a facility manages infection outbreaks—a critical component of healthcare delivery in high-risk environments like nursing homes. Facilities that effectively manage these aspects are likely to be more efficient in their overall operations, thus these variables serve as key indicators of preparedness and response effectiveness.

4.2.2 Results for all nursing homes in PA state

In this section, the same analysis was done for all nursing homes in PA. The accuracy of the ML models is seen in Table 4. The Random Forest technique has again provided the most accurate results in terms of all performance metrics.

Table 4 Performance results of ML models

Model	Sensitivity	Specificity	Accuracy	AUC
Support Vector Machine	0.63	0.82	0.74	0.82
Neural Network	0.72	0.78	0.75	0.84
Decision Tree	0.71	0.74	0.73	0.74
Random Forest	**0.78**	**0.87**	**0.83**	**0.91**

Information fusion-based sensitivity analysis results (Fig. 8) showed that the ‘Total Residents COVID-19 Confirmed Cases’ has the highest impact on the prediction of the efficiency of the nursing homes, and the ‘Number of Tests on Staff’, ‘Total Resident COVID-19 Deaths’, and ‘Overall Rating’ follow this variable.

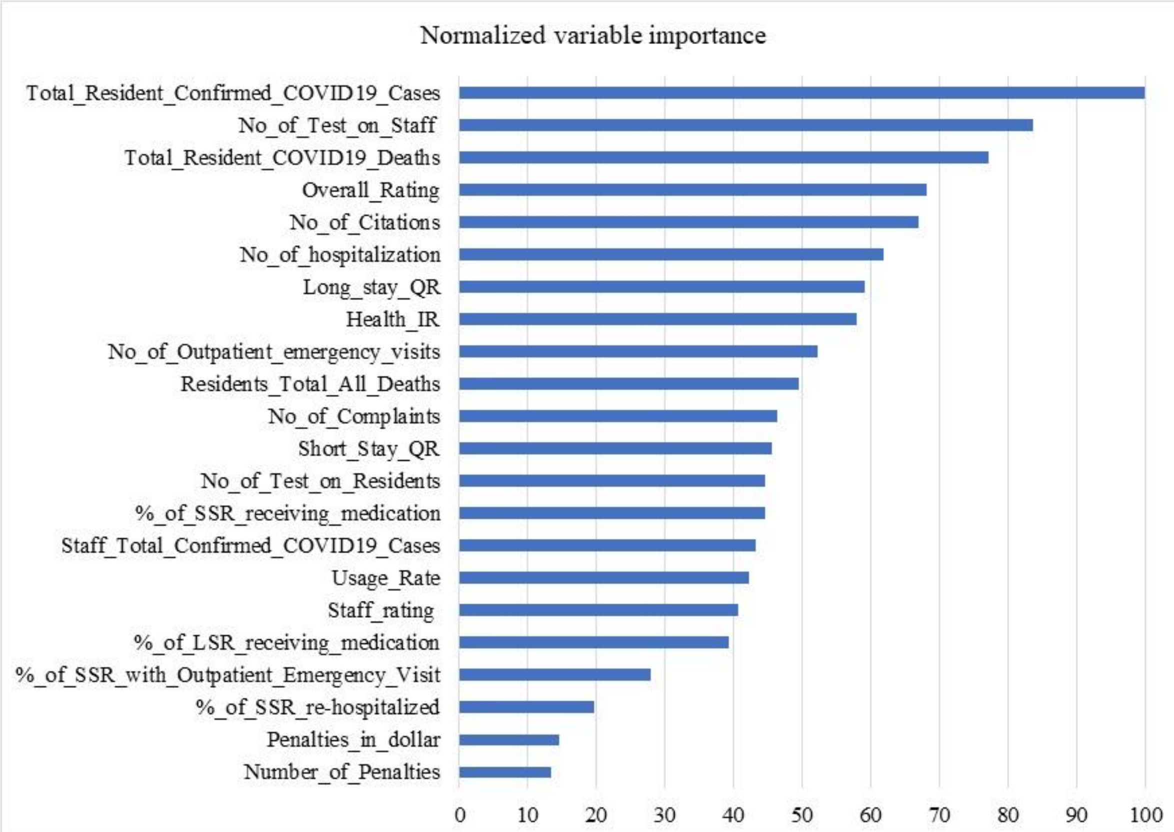

Fig. 8 Variable importance results of the information fusion model

5 Conclusions and Future Directions

In this study, we assessed the performance of the nursing homes in the three regions of PA and determined the efficient and inefficient nursing homes relatively by using Data Envelopment Analysis (DEA) model. We also proposed a hybrid model that integrates DEA and ML techniques to provide a prediction model that predicts the efficiency of a new nursing home and determined which variables have the highest impact on the efficiency prediction by using an information fusion-based sensitivity analysis that combines the results of each ML model. This is crucial for the administrators to be aware of the efficiency of the nursing home and know how to make it more efficient proactively.

We conducted a regional analysis to investigate potential variations in the factors influencing nursing home efficiency across each region. Our aim was to discern how to enhance the performance of inefficient nursing homes. The comparative analysis of the DEA results revealed that certain inputs hold substantial significance in the performance assessment of nursing homes across all regions. Specifically, the variables 'Number of Citations' and 'Number of Complaints' emerged as highly influential factors, indicating that these areas require more substantial improvements compared to other inputs to enhance the efficiency of inefficient nursing homes. Additionally, variables related to COVID-19, such as 'Total Resident COVID-19 Deaths' and 'Total Resident COVID-19 Confirmed Cases' followed closely in importance. These findings suggest that inefficiencies often stem from multiple interrelated factors. Key among these is the quality of care, which is affected by inadequate staffing levels and insufficient training, leading to substandard care practices and increased incidents of neglect or abuse (Zimmerman et al. 2020; Castle and Ferguson 2010). Additionally, operational inefficiencies such as poor management practices, ineffective resource use, and inadequate emergency preparedness are prominent, particularly during crises such as the pandemic (McGarry et al. 2020). This situation is exacerbated by challenges in compliance with evolving healthcare regulations, where facilities struggle to implement new standards effectively (Ouslander and Grabowski 2020)). The analysis also highlighted problems with infection control practices, emphasized by the spread of COVID-19 within facilities. Inadequate disease prevention protocols, insufficient personal protective equipment, and poor adherence to safety measures have been critical in driving the spread of the virus, indicating fundamental lapses in routine and emergency healthcare practices (Stone et al. 2021). Moreover, the complex health conditions of residents and the inefficient allocation of resources further impact the quality and efficiency of care. Facilities with a high proportion of residents with severe health conditions face additional challenges in managing care effectively, which, along with a lack of investment in quality improvement initiatives and modern healthcare technologies, leads to poorer outcomes (Barnett and Grabowski 2020). So, to improve further, nursing homes should focus on continuous enhancement strategies even when high efficiency is reported. Specific actions could include refining staff training programs to address frequent complaints and citations, bolstering infection control measures to reduce COVID-19 cases and deaths, and improving medication management practices to decrease emergency visits. Additionally, adopting regular feedback mechanisms involving residents and staff can help identify areas for improvement that are not immediately apparent through quantitative analysis alone. Ultimately, by broadening the scope of DEA models to include qualitative measures of performance, nursing homes can achieve a more comprehensive and meaningful interpretation of efficiency that aligns with the overall goal of improving resident care and quality of life.

The results of the prediction model integrated with the DEA model (DEA+ML) also provided a very valuable advantage for the administrators. The DEA+ML hybrid model results showed that quality-related variables including Quality Rating, Short Stay QR, and Long Stay QR are the most significant variables in the efficiency prediction and COVID-related variables including Total Resident COVID-19 Confirmed cases, Total Resident COVID-19 deaths and Number of tests on residents follow these variables. Quality related variables reflect resident experiences and outcomes, which are central to evaluating facility performance. High quality ratings often correlate with better resident satisfaction and overall operational efficiency. Thus, their significance in predicting efficiency is not only expected but crucial for any comprehensive analysis (Castle and Ferguson 2010). In addition, COVID related variables reflect how well a facility manages infection outbreaks—a critical component of healthcare delivery in high-risk environments like nursing homes. Facilities that effectively manage these aspects are likely to be more efficient in their overall operations, thus these variables serve as key indicators of preparedness and response effectiveness (Abrams et al. 2020).

Our study provides insightful observations into the inefficiencies of nursing homes within Pennsylvania, categorized by regions. While these findings offer specific insights into the local context, their applicability to other locations or during different pandemics requires cautious extrapolation. The assessment of nursing home performance is a significant global concern, applicable not only in developed countries but also in developing nations. The need for Long Term Care (LTC) facilities is growing globally due to increasing life expectancy and the rising proportion of elderly individuals. This need is particularly urgent in developing countries, where traditional family support systems have weakened over time, necessitating more LTC facilities to cater to the elderly population (Adamek and Balaswamy 2016; WHO 1995). So, the underlying healthcare infrastructures, demographic characteristics, regulatory environments, and even the prevalence of various diseases can significantly differ from one location to another. Such differences may influence the performance metrics and the observed inefficiencies in ways not captured within the scope of our current analysis. Moreover, the pandemic's unique nature—the specific virus involved, the rate of its spread, and the public health response—can also affect the generalizability of our results. For instance, a pandemic causing more severe outcomes in younger populations might impact nursing home operations differently than COVID-19, which predominantly affected older adults.

To bridge these gaps in generalizability, future research could replicate our study framework in varied geographic settings and under different pandemic scenarios or even other Long Term Care issues including Alzheimer's disease, mental illness, hearing loss, blindness, depression, and other health conditions prevalent among the elderly. Investigating these areas can reveal further opportunities for improvement in LTC facilities. This approach would allow for comparative analyses that could confirm or refine our initial findings, providing a broader understanding of universal versus context-specific drivers of efficiency in nursing homes. Ultimately, such studies would enhance the robustness of our conclusions and better inform global strategies for managing long-term care facilities during public health crises.

In essence, this study represents a starting point for a broader exploration of nursing home efficiency and healthcare challenges, with the potential for global application and the enhancement of long-term care services. Moreover, this study is valuable for providing nursing home administrators with new insights into how nursing homes are performing when considering COVID-related inputs and outputs. Furthermore, the DEA results can be used as a roadmap to how inefficient nursing homes can improve their performances. Because this is the first study that assesses the performance of nursing homes against pandemics, it will be an important contribution to the existing literature.

Author contributions

All authors contributed near equally to the development of the study and writing of the manuscript.

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