Exploring Changes in Nursing Facility Staffing Levels Using Data Science

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Introduction

The quality of care in skilled nursing facilities (SNFs) is of great concern to many in the United States who have elderly relatives or other loved ones with disabilities or chronic conditions who must stay at them, away from home, for short rehabilitation (up to 100 days may be covered, with conditions) or for long periods of time (Medicare.gov, 2025). SNF patients are often vulnerable (Kim et al, 2022) and a great amount of trust is placed in SNFs to treat them well by attending to their daily needs and giving them the specific medical care they require. This care can include round-the-clock outpatient medical care and rehabilitation to help patients recover from illness, injury, or surgery, which is often known as post-acute care (Campbell Britton et al, 2020). SNFs also offer physical and occupational therapy, speech-language pathology, and daily living assistance such as helping patients bathe, eat, and dress, providing medication reminders and administering medication, and generally monitoring patients' health (Medicare.gov, 2025). SNFs can employ certified nursing assistants (CNAs) to help with more of these simple daily tasks, but SNFs are set apart as facilities by employing registered nurses (RNs), licensed practical nurses (LPNs), and even physical and occupational therapists to provide more expert and specialized care (Heiks et al, 2022).

Reports of stories of neglect, fraud, and abuse come from nursing facilities either via official reporting or word-of-mouth in our personal lives, yet still, negligence and abuse often go unreported (Hawes, 2003). When it comes time to choose a facility to send a patient to, family or other caregivers feel pressured to choose a place with a good reputation (Pesis-Katz et al, 2013). However, depending on conditions attached to the patient's healthcare plan, whether that be Medicare, Medicare Advantage (Grabowski et al, 2023), or Medicaid for example (Sharma et al, 2020), patients may not have the freedom to choose any facility they desire. SNFs also choose residents based on the factors of their prior hospitalizations (Campbell Britton et al, 2020) and may reject patients on that basis. Facilities also need to have capacity for a new patient. This can make selection difficult, especially if the available facilities include those with reported citations, or are known for generating complaints when their staff is stretched thin, for example.

SNFs need to apply to be eligible to take Medicare patients and receive government funding by going through a certification process. An SNF can be privately owned and for-profit, or nonprofit (Ryskina et al, 2024). Facilities must keep up a required standard of care, including thorough documentation, safety, quality patient medical and daily care, having licensed professionals on staff, and of particular importance to this report, adequate staffing level (Medicare.gov, 2025). While "adequate" staffing has been a standard for a while, until a federal rule was made in 2024 that set a required minimum number of staffing hours per resident per day, there was no number attached to the expectation (The Federal Register, 2024). Facilities may gain access to more government funding if they choose by broadening the scope of their patients, such as providing Medicaid accommodations (National Academies of Sciences, Engineering, Medicine, Health, Medicine Division, Board on Health Care Services, & Committee on the Quality of Care, 2022). However, a breach in any of the standards an SNF's license is predicated upon may result in a citation, which will be publicly available data (Data.CMS.gov, 2024). These breaches coincide with what the literature reports as "deficiencies." Citations and deficiencies in standards over an extended period of time may result in an investigation, which can lead to an SNF losing its Medicare license and the associated funding (Medicare.gov, 2025). These breaches and citations will lower an SNF's Five Star Rating if not corrected (Medicare.gov, 2025). The Five Star Rating is supplied by the Centers for Medicare & Medicaid Services (CMS) using measures associated with the standards and gives patients and their caregivers a publicly available rating from 1-5 stars for each Medicare licensed facility (CMS.gov, 2025).

However, licensed facilities with low star ratings remain with funding intact, and highly rated facilities may still carry citations or provide poor care anyway. Different facts about SNFs underlie the "true" quality and potential patient risks associated with a facility. This study seeks to explore how changes in a key nursing facility datapoint, changes in staffing levels, are associated with other indicators of SNF quality and patient outcomes in order to surface which SNF quality factors appear most highly associated with and most strongly affected by staffing levels.

Background and Literature Review

Research on the topic of SNF quality has been done extensively, but is disseminated across many viewpoints on how to measure quality for the 15,000 skilled nursing facilities in the U.S. (Kim et al, 2022). These include studies on the CMS Five Star Rating itself (Konetzka et al, 2015), staffing levels (Martin, 2015), the differences between nonprofit and for-profit facilities (Ryskina et al, 2024), and more. Many of these measures are intertwined. For example, staffing levels may influence the Five Star

Rating, but the effect may be more complex based on whether or not the facilities in question are nonprofit or for-profit (Zuckerman et al, 2019). For-profit facilities may feel incentivized to maintain low staffing levels for monetary reasons, such as when for-profit facilities change ownership and cut costs by laying off staff (Ryskina et al, 2024).

To briefly touch on more work done here, it's been found that low/insufficient staffing levels are associated with the appearance of deficiencies in an SNF (Chidambaram et al, 2024) and to poorer health outcomes for patients (Martin, 2015). For-profit facilities are more highly associated with lower quality facilities (Kim et al, 2022). Medicaid patients, who make up the majority of long-term care residents (Chidambaram et al, 2024), are highly associated with acceptance to one-star facilities, and those facilities are often larger and for-profit (Zuckerman et al, 2019). Higher rated facilities may tend to have higher staffing levels, but if a facility lays off staff, the rating doesn't go down much (Zuckerman et al, 2019), owing to the numerous datapoints that make up the Five Star Rating. The relationships between these more well-known or high-profile datapoints can be significant but their effects on one another may be small. We feel that choosing a datapoint that is more directly related to patient care and facility management, such as staffing, is the better choice of dependent or "target" variable for analyzing which factors stand out when staffing levels change.

For our purposes, research on the quality of SNFs in recent years can be divided into three parts: research prior to COVID, during COVID and the lockdown period, and post-COVID. In the prior-COVID period, there was general interest in the quality of SNFs and is viewed by this report as the default or "baseline" of research as well as the baseline of facility quality itself. The institution of the Improving Medicare Post-Acute

Care Transformation (IMPACT) Act in 2014 required facilities such as SNFs to provide more plentiful and standardized data on facility facts and patient outcomes (CMS.gov, 2025), making quantitative analysis more possible and consistent. However, the COVID-19 pandemic can be seen as a more recent inflection point. During COVID, there emerged a wealth of public interest in patient care in the wake of reports of illness and infections sweeping through places such as retirement homes, and of course, SNFs (Kim et al, 2022). This raised concerning questions about whether facilities' staff were adequately trained or at adequate levels to prevent infections and to prevent those infections from spreading.

The question of adequate staffing is a balance of several datapoints: the number of nurses compared to how many beds there are at a facility, and therefore, how many hours of care a patient gets per day, and conversely, how many minutes a nurse can spend on a patient per shift. Until the new federal rule made in 2024, there was no numerical requirement for this, so there was likely gray area in what constituted "adequate" staffing. (The rule is now 3.48 hours of nursing care per resident per day, 0.55 hours from RNs, and 2.45 hours from CNAs, with at least one RN needing to be on-site 24/7 (The Federal Register, 2024).) Facilities are required to have certain specialists on staff to provide nutritional care, therapeutic care, and there should be a licensed nurse leading each shift (Medicare.gov, 2025). Facilities with higher staffing have been associated with better care and better patient outcomes outlined in the CMS Minimum Data Set (MDS), such as lower prevalence of pressure ulcers (bedsores) and lower post-acute transfers, among other indicators (White et al, 2023). Yet despite these standards, individual nurses reported feeling rushed and less able to provide necessary care (Govasli at al, 2020). This was also a period of shifting employment levels due to fear of COVID in the workplace (Kim et al, 2022) and climbing wages in the United States (Federal Reserve Bank of St. Louis, 2025), a time when nurses may have changed jobs (Heiks et al, 2022), which may have made it difficult for SNFs to find staff and keep them. A study focused on COVID-19 infection rates and deaths in nursing homes in Illinois found that while staffing levels didn't necessarily change much from the pre-COVID period to the COVID period, there was a relationship between COVID infections among the staff and the rise in infections in nursing home patients, especially in lower-rated facilities (Kim et al, 2022), which raises questions about facility quality and policies for staff. (A KFF report published 2 years later suggests that the counterintuitive finding of more staff hours per resident in the 2020-2021 period is due to resident numbers decreasing more quickly than staff hours did (Chidambaram et al, 2024).)

In the wake of this spike in interest and research, our attention now turns to what staffing levels and overall facility quality look like in the current "post-COVID" period. A Kaiser Family Foundation (KFF) report has found that the number of residents in SNFs has decreased by 10% since the pandemic due to the number of deaths – over 37% of deaths from COVID-19 in the U.S. were from people in long-term care facilities by the end of 2020 (Kim et al, 2022) - at facilities during that period, and many patients have opted for in-home care instead. And yet, the amount of time given to each patient in a facility has declined 8% from 2015 to 2024. In addition, the average amount of deficiencies found in facilities – leading to citations and the conditions that could cause a Medicare licensed facility to lose its license – have increased, and the share of facilities with deficiencies has increased from 17% to 28% in the same period nationwide. And lastly, staffing levels are below pre-pandemic levels (Chidambaram et al, 2024).

These are troubling statistics, combined with the fact that the U.S.'s aging population (Caplan, 2023) means that the Medicare system will likely be seeing more patients in need of nursing care in the near future. Findings continue to point to staffing and staffing levels as a key indicator (Chidambaram et al, 2024) of the quality of patient healthcare outcomes (Martin, 2015). While past literature is often inconclusive about which SNF quality factors drive staffing levels, and vice versa, data science can help us untangle the myriad datapoints that make up the general picture of SNF quality and how that general picture relates to staffing levels now being lower than they were pre-COVID. This can help us know what to look out for in terms of nursing facility quality in this post-COVID period of shifting statistics and changing administrations. With so many variables at play, we first need to know which of these many datapoints is most closely related to, or most strongly affected by, changes in staffing levels from pre-COVID to post-COVID. Feature selection, or feature importance analysis, methods common in data science exploratory studies, will aid us in this exploration.

Methodology

This study poses the question: "Which variables help illustrate the change in staffing levels from pre-COVID to post-COVID?" We believe that exploratory data science, tree model building, correlation analysis, and feature selection will help us answer this question.

This study employs a qualitative research design using quantitative data science methods to analyze data on SNF staffing levels and many other facility qualities per facility per reporting year in the U.S. Secondary data is obtained primarily from the CMS government website. There are a few datasets of interest:

- MDS Quality Measures
    - "Quality measures that are based on the resident assessments that make up the nursing home Minimum Data Set (MDS). Each row contains a specific quality measure for a specific nursing home and includes the 4-quarter score average and scores for each individual quarter."
- Medicare Claims Quality Measures
    - "Quality measures that are based on Medicare claims data. Each row contains a specific quality measure for a specific nursing home and includes the risk-adjusted score."
- Health Deficiencies
    - "A list of nursing home health citations in the last three years, including the nursing home that received the citation, the associated inspection date, citation tag number and description, scope and severity, the current status of the citation and the correction date. Data are presented as one citation per row."
- Provider Information

- “General information on currently active nursing homes, including number of certified beds, quality measure scores, staffing and other information used in the Five-Star Rating System. Data are presented as one row per nursing home.”

The CMS offers all of these datasets by report year monthly snapshots from 2018-2025. Each dataset can be combined or “joined” by the CMS Certification Number (CCN), which is a unique identifier for a facility. The snapshots chosen for this study are: the earliest available 2018 snapshot (January 2018) to represent the pre-COVID era, and the March 2025 snapshot to represent the current post-COVID era. To be eligible for our dataset, each facility needed to have existed, reported, and been Medicare/Medicaid licensed in both snapshots.

The prior and post datasets are combined by joining on the CCN and adding the prior dataset’s variables as new uniquely named columns to the post dataset.

The dependent variable in this study is defined as “Lower_Staffing.” This is a facility’s pre-COVID staffing hours, “Adjusted Total Nurse Staffing Hours per Resident per Day” from the Provider Information variables, subtracted from the facility’s post-COVID staffing hours. Whenever the resulting difference in staffing hours is less than a chosen cutoff – 0 for the baseline analysis, -1.0 for a comparative analysis to be discussed later – Lower_Staffing is 1, meaning the facility’s staffing levels are lower than they were pre-COVID. Otherwise, Lower_Staffing is 0. This creates a binary dependent variable, which both simplifies the analysis and allows us to manipulate the definition of lower staffing for easy further analysis after changing the aforementioned cutoff during the research process.

As many as 190 independent variables are included as candidate “important” variables, also known as “features” in data science, pulled from the Provider Information, Health Deficiencies, Medicare Claims Quality Measures, and MDS Quality Measures datasets. These are a mix of nominal, ordinal, and interval features. Each datapoint is transformed according to what the feature represents with the rule that any categorical variable, be it nominal or ordinal, is dummy-encoded in order to aid the model training process and to make it simpler to pluck important granular datapoints from the results. Some features are calculated from other features, such as the number of months since a facility was Medicare/Medicaid licensed as of March 2025. Such features were added in an attempt to give a model as much information as possible. Feature calculation was kept to the four aforementioned datasets to somewhat limit the scope of this study due to time limitations, but further study would certainly open up the featureset to even more data provided by the CMS.

To begin the feature importance analysis process, a tree model – specifically, a Light Gradient Boosted Model (Light GBM) - is trained on 190 features with a Lower_Staffing cutoff of 0, meaning that any facility that had any magnitude of negative change in its staffing levels from pre-COVID to post-COVID is considered as a lower staffing facility in the model. Light GBMs are tree models that use a complex decision tree design that intelligently creates its own optimal splits in the tree nodes, and attempts to “self correct” its model fitting “mistakes” throughout the fitting process. Light GBMs were created to computationally run faster than other GBMs, such as Extreme

GBMs, use histograms to optimize splits in the decision tree, and are less prone to over-fitting (Features, 2025). Ultimately, a tree model such as a Light GBM can be used in feature importance analysis to extract which features ended up “teaching” the model the most useful information about how to fit correctly to the dependent variable (Hu & Li, 2022), or in other words, how to correctly identify which facilities had lower staffing and which ones didn’t.

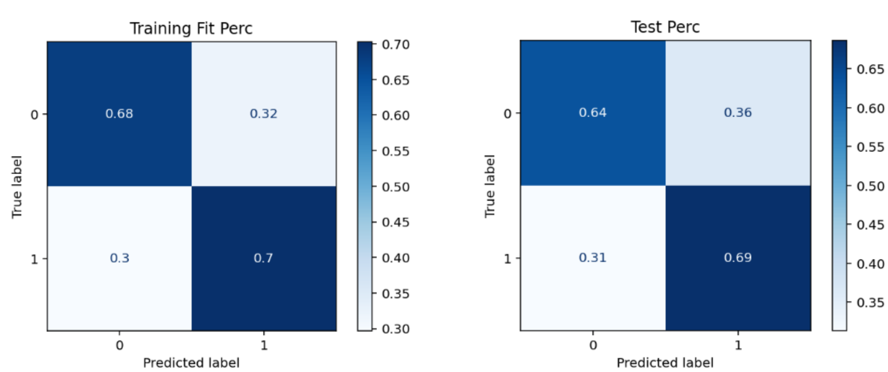
This study uses the Python programming language and the sci-kit learn library to extract important features from the trained Light GBM model. We also use a graph of calculations called Shapley Values which shows similar information on which features were most informative to the model, except with additional useful details about these features, such as the direction and strength of the independent variables’ relationships to the target variable across all values of those independent variables. To help us determine whether the features were intelligently selected by the model fitting process, we test the model on a holdout dataset of facilities that were not seen by the model during the training process, and evaluate those results. We also use correlation maps to perform correlation analysis on highly correlated features, which helps us cull independent variables that are likely too closely related to the Lower_Staffing dependent variable to be informative. This culling helps expose important variables that are less circularly related to Lower_Staffing, providing opportunities for further analysis and insights.

The above process is repeated for a more selective cutoff staffing reduction level of -1.0. This results in a dataset where facilities that had a magnitude of change in staffing levels of less than 1.0 – either in the positive or negative direction – are dropped from the dataset, leaving only facilities with more notable staffing level decreases or increases. This helps confirm the effect of previously identified variables and allows us to determine if the model is truly discerning between lower and higher staffing level change facilities, or if initial feature importance results were simply influenced by noise from facilities that didn’t change much about their staffing levels.

This feature importance analysis process involves examining results at multiple points using multiple models, but allows us to peel back layers of analysis to reveal more relationships between the many facility features and whether or not those facilities lowered their staffing levels. This helps us think through why these associations might exist and what the facility environment could be like and what the impacts could be when facilities change their staffing levels.

Results

From the prior-COVID to the post-COVID snapshot, staffing levels in the dataset fell from about 3.98 to 3.89 staffing hours per resident per day. The first Light GBM we train and test uses 190 features and a staffing level cutoff of 0. 53% of the 14,500 U.S. facilities had lower staffing levels post-COVID compared to pre-COVID.



Figures 1 and 2. Train and test results of Light GBM model with cutoff 0, 190 features.

In these confusion matrices, the top row of the matrix shows the percentage of facilities with higher/the same staffing that the model got right and wrong. The bottom row shows the percentage of facilities with lower staffing. The first confusion matrix we see shows how well the model fit to the data. The second one shows how well the model tested on a holdout dataset, meaning, how good it was at identifying whether facilities it had not seen during the training process had lower staffing levels or not. We see that the model fits and tests only fairly well on the data, but is still significantly better than a coin toss. This is our baseline model that we improve on later.

Next, we extract the Light GBM's important features using the scikit-learn library. The features listed at the top of the graph gave the model the most information about how to fit to the dependent variable. Unsurprisingly, variables that use staffing levels in their calculations, such as the 5-star staffing rating, staff turnover, patients-to-beds ratio, and others were informative.

Below is a table to aid in referencing the MDS quality measure codes and the quality measure descriptions associated with them, as these will play into further results in the feature importance graphs:

Measure code	Measure Description
401	Percentage of long-stay residents whose need for help with daily activities has increased
404	Percentage of long-stay residents who lose too much weight
406	Percentage of long-stay residents with a catheter inserted and left in their bladder
407	Percentage of long-stay residents with a urinary tract infection
408	Percentage of long-stay residents who have depressive symptoms
409	Percentage of long-stay residents who were physically restrained
410	Percentage of long-stay residents experiencing one or more falls with major injury

415	Percentage of long-stay residents assessed and appropriately given the pneumococcal vaccine
419	Percentage of long-stay residents who received an antipsychotic medication
430	Percentage of short-stay residents assessed and appropriately given the pneumococcal vaccine
434	Percentage of short-stay residents who newly received an antipsychotic medication
451	Percentage of long-stay residents whose ability to walk independently worsened
452	Percentage of long-stay residents who received an antianxiety or hypnotic medication
454	Percentage of long-stay residents assessed and appropriately given the seasonal influenza vaccine
472	Percentage of short-stay residents who were assessed and appropriately given the seasonal influenza vaccine
479	Percentage of long-stay residents with pressure ulcers
480	Percentage of long-stay residents with new or worsened bowel or bladder incontinence

Table 1. MDS quality measures dataset quality code descriptions

Here is a similar table for the Medicare Claims quality measures dataset:

Measure Code	Measure Description
521	Percentage of short-stay residents who were rehospitalized after a nursing home admission
522	Percentage of short-stay residents who had an outpatient emergency department visit
551	Number of hospitalizations per 1000 long-stay resident days
552	Number of outpatient emergency department visits per 1000 long-stay resident days

Table 2. Medicare Claims quality measures dataset quality code descriptions

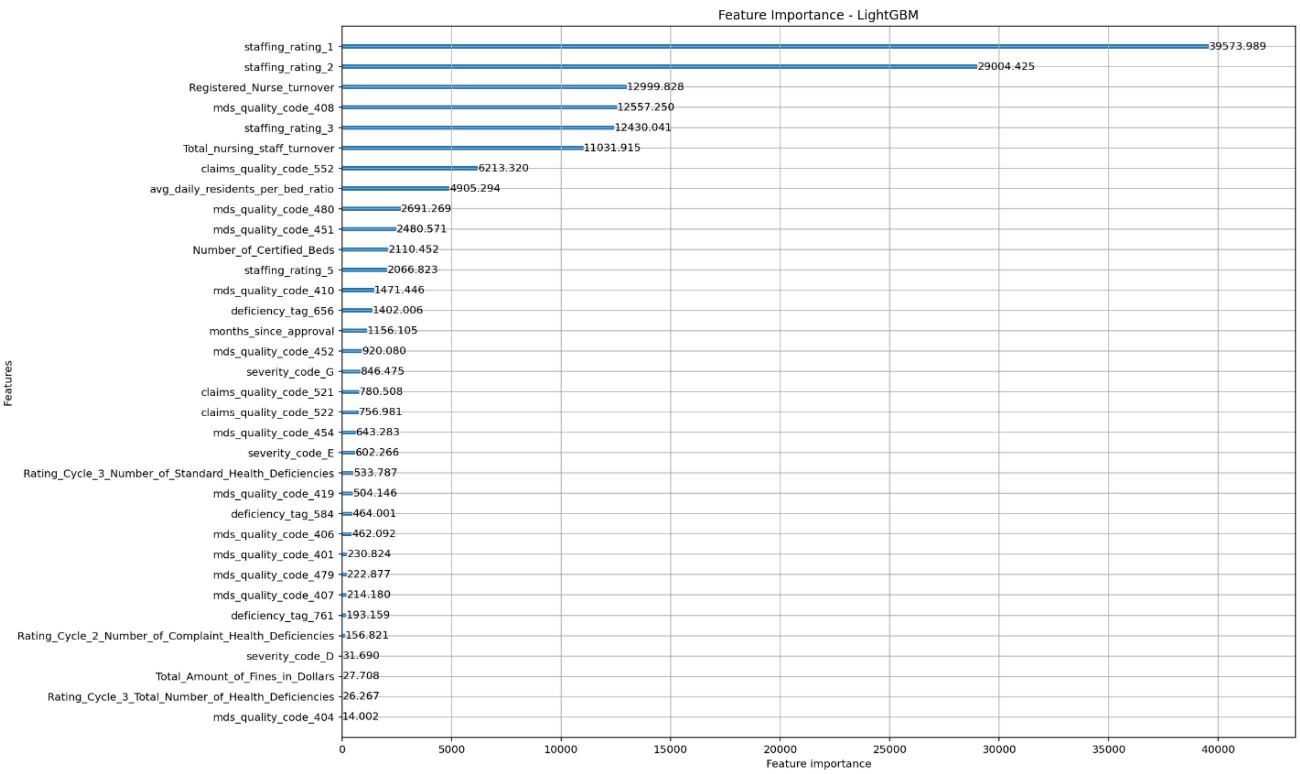


Figure 3. Light GBM Model cutoff 0 with 190 features feature importance.

The Shapley graph gives us similar results, but also shows whether high values per independent variable (red) or low values (blue) increase the likelihood of lower staffing (trends to the right) or decrease the likelihood (trends to the left). Dummy encoded variables with the positive marker, 1, would be in red (high value) for example, while the 0 value would be blue (low value).

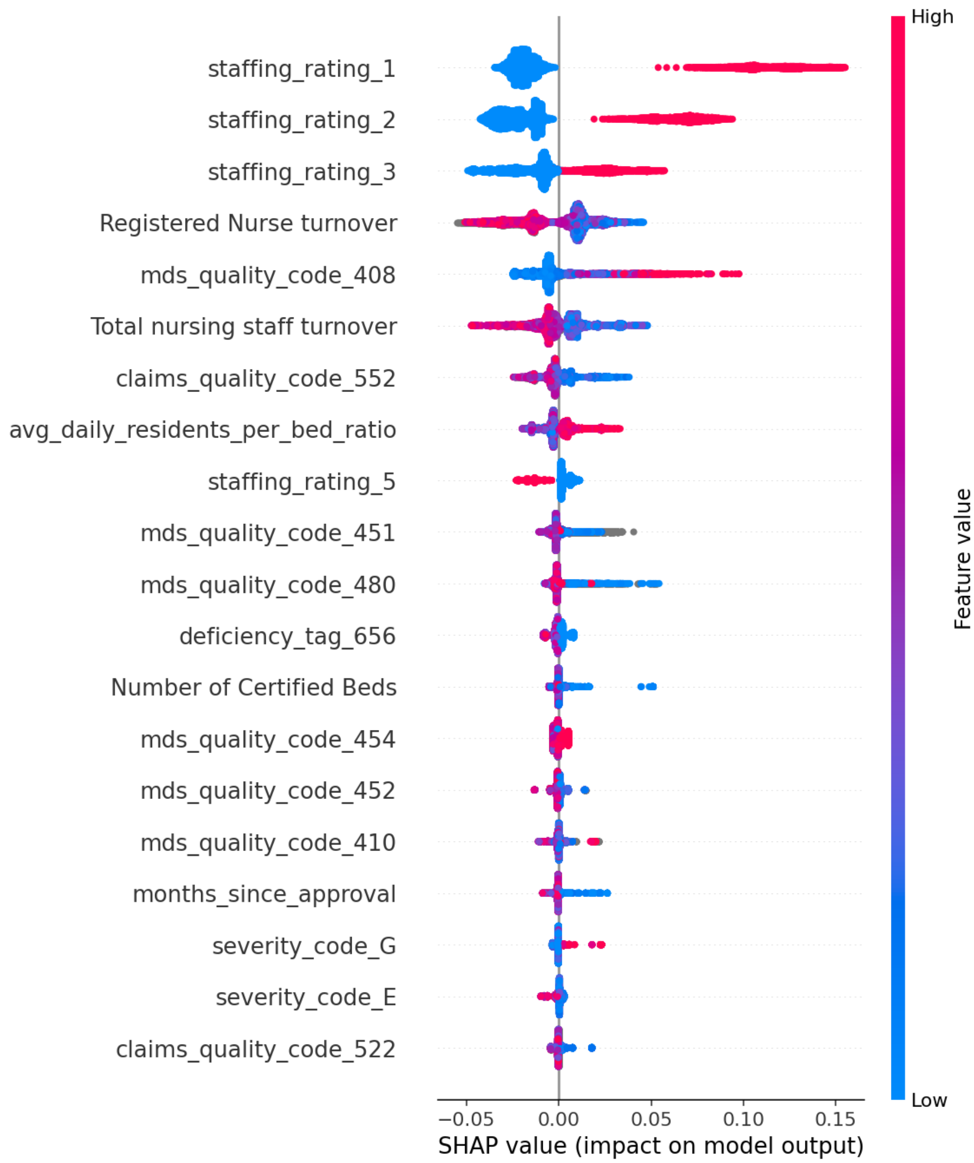


Figure 4. Light GBM model cutoff 0 with 190 features Shapley graph.

When we look at the correlation map and narrow down the visualization to the most important features extracted from the Light GBM for readability's sake, we begin to suspect circular relationships:

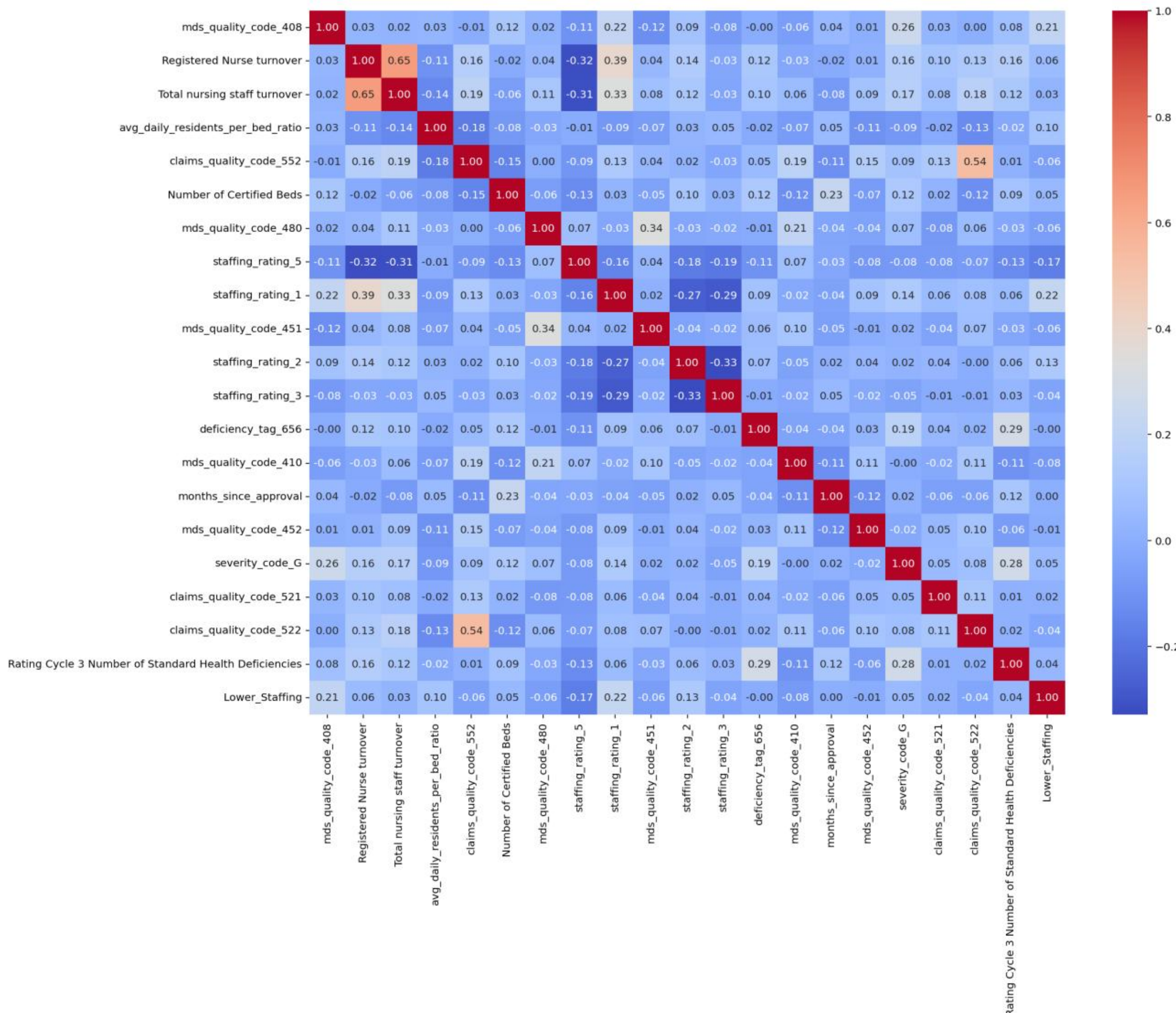


Figure 5. Light GBM model 0 cutoff with 190 features correlation map.

Many of the staffing, turnover, and rating-related variables are not egregiously correlated, but they are consistently correlated. Logic tells us that behind the curtain, they are used to calculate one another. The high staffing rating of 5 is correlated with low turnover, likely because turnover is used in the 5-star staffing rating calculation. Conversely, high turnover is correlated with the lowest staffing ratings of 1 and 2 stars. Lastly, logic tells us that lowered staffing levels over time will factor into low star rating calculations.

So when we cull obviously correlated variables, we end up with 160 features and we get see the independent variables that don't use staffing in their own calculations:

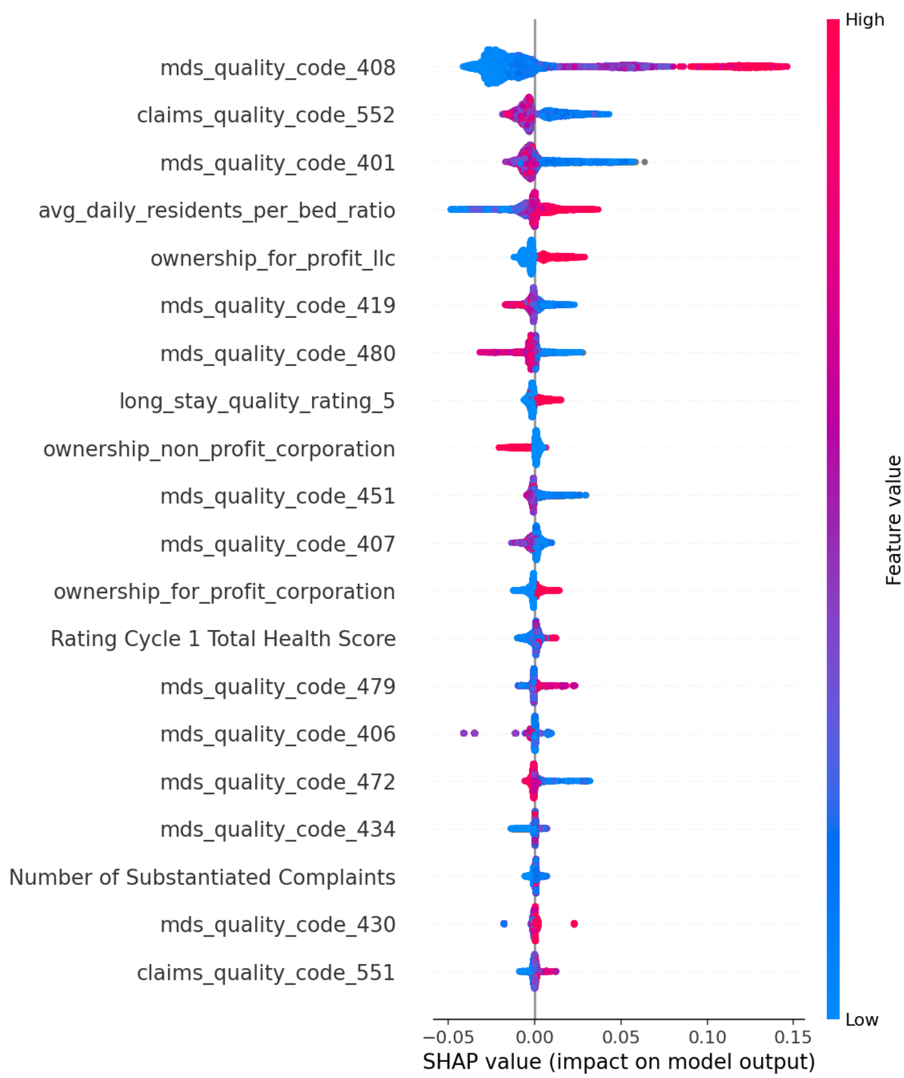
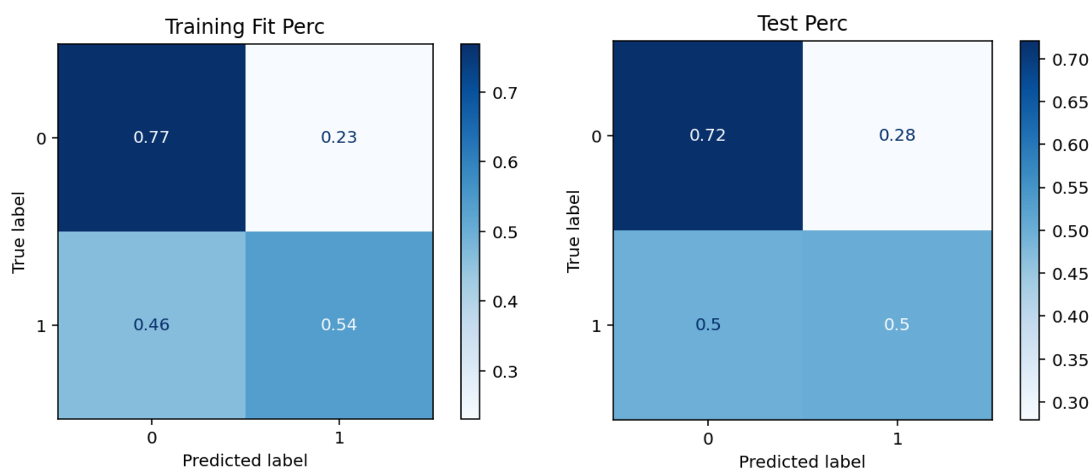


Figure 6. Light GBM model 0 cutoff with 160 features Shapley graph

An MDS dataset quality code, code 408, the percentage of residents showing symptoms of depression during a long-term stay, is now most highly associated with reduced staffing levels over time. Several quality codes representing an array of patient health outcomes stack up in the list of most important features on the Shapley graph, outpacing health citation delinquency codes, facility details such as Medicare vs. Medicaid facilities, reported fines, health inspection ratings, and many other variables.

Ownership type also ranks high in the important features. For-profit facilities are highly associated with lowered staffing levels.

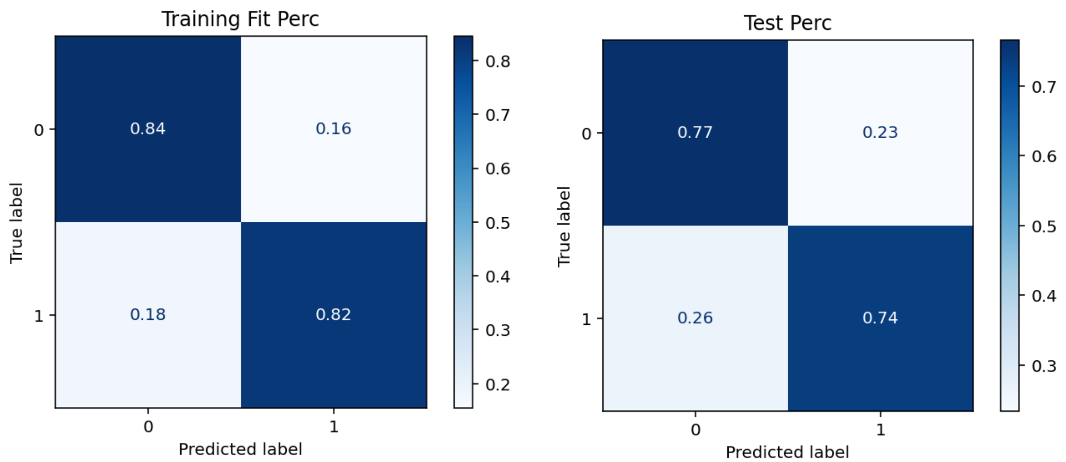
Taking away the inter-correlated staffing variables lowers the test performance of the model:



Figures 7 and 8. Train and test matrices of Light GBM model cutoff 0 with 160 features

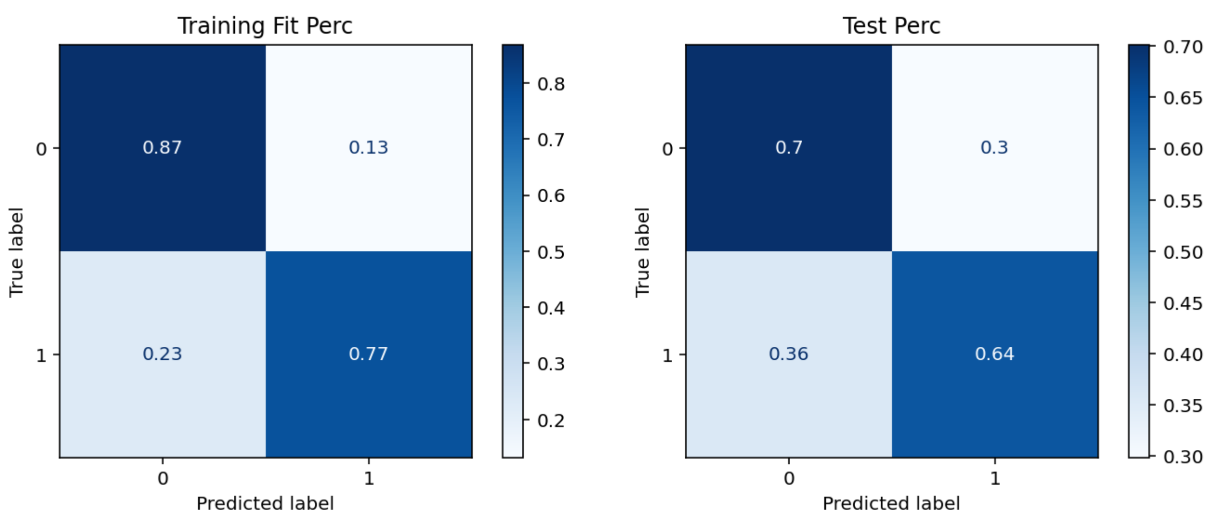
Though using the model for prediction isn't our purpose and we are instead only looking for important features surfaced by the model fitting process, the next round of results can show whether these features in the secondary "stripped" model hold true when we remove facilities from the dataset that didn't change their staffing levels much in either direction.

So lastly, when we change our staffing level cutoff to -1.0 and train on all 190 features once more, we see the strongest and most “predictive” model, showing that changing the cutoff produces a better model with clearer results:



Figures 9, 10. Train, test matrices of Light GBM cutoff -1.0 with 190 features

And finally, when we again take away the inter-correlated staffing features and keep the -1.0 cutoff, the model is stronger than the 0 cutoff:



Figures 11, 12. Train, test matrices of Light GBM cutoff -1.0 with 160 features

The same quality codes representing patient health and the facility organization type are once again the most important features highly associated with lowered staffing levels, persisting these relationships between models with different cutoff levels:

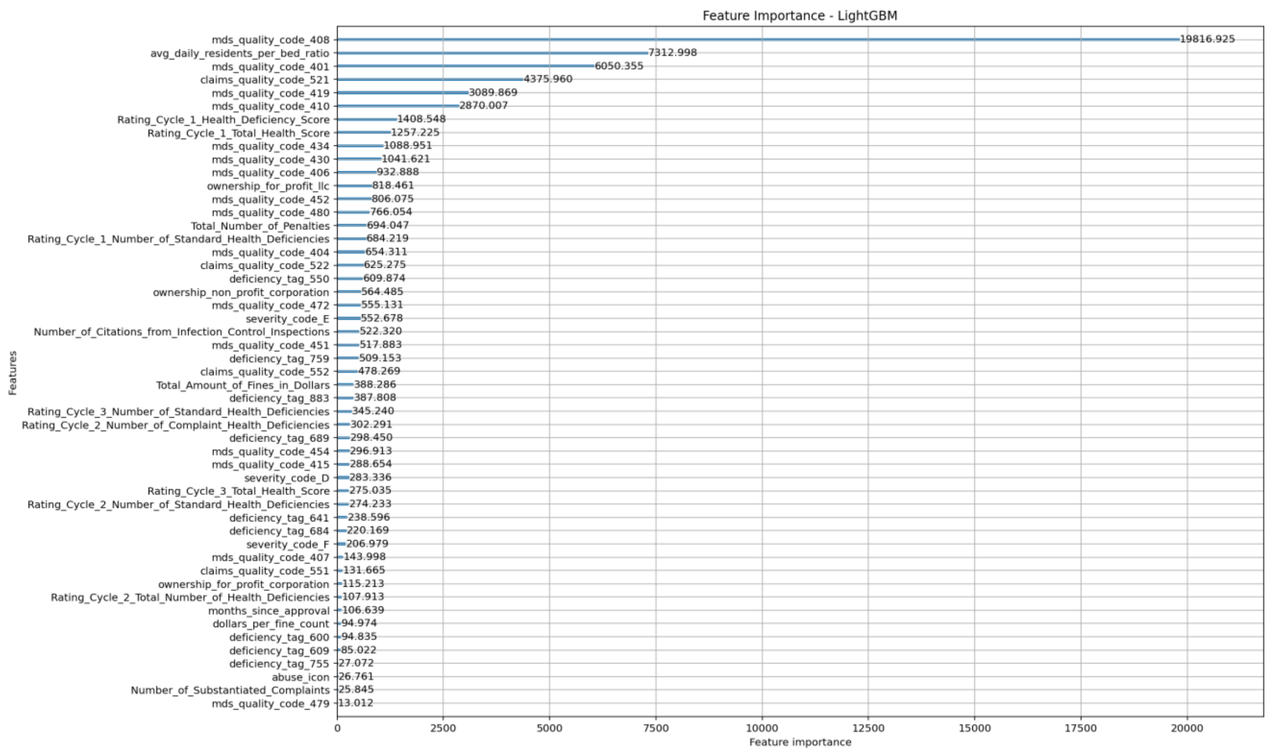


Figure 13. Light GBM cutoff -1.0 with 160 features feature importance

We see similar results once again with our final Shapley graph:

Figure 14. Light GBM cutoff -1.0 with 160 features Shapley graph

The final model with the severe -1.0 staffing level cutoff contains about 2,800 facilities. 59% of those facilities lowered their staffing levels.

Discussion

While it comes as no surprise that independent variables that use staffing in their calculations greatly help the baseline model to identify facilities that lowered their staffing, there are still some notable insights to identify here in the model with 0 cutoff and all 190 features.

Firstly, the concept of the Lower_Staffing dependent variable does not inherently take into account whether a facility's current post-COVID staffing level is "adequate" or not. There is the possibility that a facility significantly reduces its staff, but that level is still "adequate." Some light is shed on this by how important the 5-star staffing rating is – especially the lowest ratings, 1 and 2 stars. Facilities that lowered their staffing levels are associated with objectively poor staff ratings as evaluated by the government. In addition, the other quality ratings, such as the 5-star overall rating, do not crack the top 20 important features, only the staffing rating does. This helps us focus on the idea of staffing levels themselves being directly related to facility quality, as prior research has shown that most 5-star quality ratings as calculated by the government are weakly related to overall facility quality except in the more extreme 1-star and 5-star cases.

We also see with the patients-to-beds ratio feature, the more patients there are compared to beds, the more closely associated a facility is with lowered staffing levels, together with a higher average number of residents per day, suggesting busier and larger facilities. This shows that facility size is a significant factor associated with facilities that lowered their staffing over time.

Once we strip away variables with staffing calculations that are obviously correlated with one another, we see that actual patient health outcomes dominate the most important features, immediately suggesting that staffing levels are highly associated with a facility's patient well-being. Long-term patients are more likely to develop symptoms of depression (code 408) in facilities that lowered staffing levels. This is the result that is by far the most clear of all the other facility variables including health outcomes in the dataset.

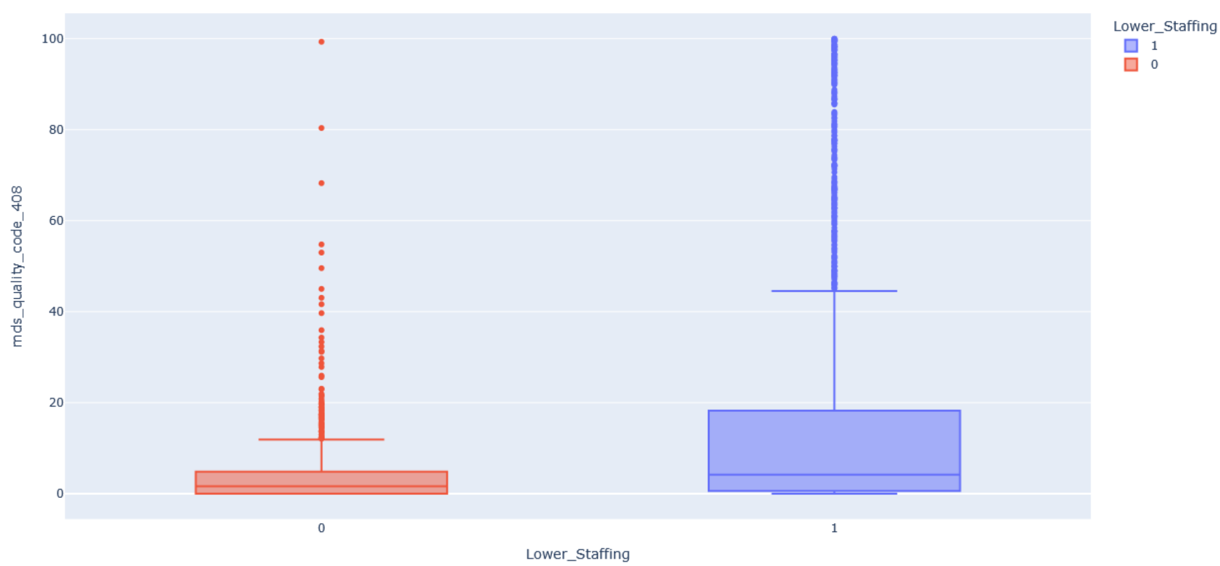


Figure 15. MDS quality code 408 box plots of NO lower staffing vs. YES

It stands to reason that long-stay residents who experience a facility lowering their staffing hours per resident per day would likely have less opportunity for daily human interaction, possibly resulting in symptoms of depression. What's notable is how much this result stands out from all other features and the fact that the direction of the association must be that first, staffing levels are lowered, and more patients with depressive symptoms follow afterward, as the reverse is much less logical.

Results of the other high-information quality codes for patient outcomes appear mixed. Facilities with lowered staffing levels are associated with long-stay patients who did not need increased help with daily activities during their stay (code 401) and with higher long-stay ratings overall, but on the other hand, they are associated with short-stay patients not receiving timely flu vaccines (code 472) and with more long-stay patients who get pressure ulcers (bedsores) (code 479). Much of this is in line with past research on facilities that keep less staff in general. Even if the positive or negative associations with quality codes to lowered staffing depends upon the quality code, overall, patient outcomes are stronger features and have a closer association with lowered or raised staffing compared to a host of other variables in the dataset, which is important to keep in mind when considering how a facility will impact the health and well-being of a patient.

Non-profit facilities are more closely associated with facilities that actually raised their staffing levels over time, with for-profit LLCs and for-profit corporations showing the inverse result, an association with lowered staffing levels. While feature importance analysis can show negative and positive relationships to a dependent variable, they cannot explain a facility's motivation behind lowering staffing levels over time, but for-profit facilities are more likely to lower staffing hours per resident per day and keep tighter patient-to-bed ratios. Organization type in these results is more important to the analysis than provider type for example (whether the facility is Medicare, Medicaid, or mixed), the facility council type, health inspection results, and more. This suggests that whether a for-profit or non-profit facility is chosen for a patient could make a significant difference in their experience during their stay.

Lastly, a couple of health citation description codes proved to be at least in the top 20 important features in the final model – codes 759 (“Ensure medication error rates are not 5 percent or greater”) and 550 (“Honor the resident's right to a dignified existence, self-determination, communication, and to exercise his or her rights”). The presence of such deficiencies is associated with facilities that lowered their staffing over time. Thus, health citations are also explanatory and important datapoints for lowered staffing facilities. This coincides with how a couple more of the top features included the presence of health deficiencies and facility penalties.

One more notable datapoint in the list of important features is the months since a facility received approval for Medicare/Medicaid services – the more recently this happened, meaning, the “younger” a facility is, the more likely the facility is to have lowered its staffing levels over time. Thus, facility “age” is also an important factor.

Taking facilities that didn’t change their staffing levels much out of the dataset removes “noise” from the data and shows that the model is able to find significant differences in the data between facilities that lowered and raised staffing. The resulting model fit and test performance is stronger even when the correlated staffing variables are taken away, and the Shapley graph shows greater separation between feature values associated with the likelihood of a lowered staffing facility and vice versa. This shows that features like the quality codes and the facility organization type are indeed important datapoints in this analysis compared to over a hundred other datapoints, as the rankings of important variables changed very little between the 0.0 and the -1.0 lowered staffing hours per resident per day cutoff.

Conclusion

A lot of data about nursing care facilities is presented to the public, and much research has been done on the relationship between individual datapoints and facility quality. The real challenge becomes sifting through all of this data and determining which analyses are more pertinent. Some research suggests that the CMS 5-star rating is not indicative of quality or of patient health, but much research agrees that facility staffing is indicative of both. And yet, from pre-COVID to the current period, nursing facility staffing levels in the US have fallen. With so much data to examine, the first step in understanding the prominent nursing facility datapoints associated with facilities with lowered staffing levels is to explore the data with data science. Using feature selection analysis, a picture coalesces: facilities that lowered their staffing levels are closely associated with poor staffing ratings as determined by the CMS, have low nursing staff turnover, have higher patient-to-bed ratios, tend to be for-profit facilities, tend to have long-stay patients who developed symptoms of depression, and overall, a mixture of quality measures gauging patient health outcomes together with facility ownership type are among the most highly explanatory and important datapoints associated with lowered staffing levels. This suggests that when a facility lowers its staffing hours per resident per day, this carries a mixture of impacts upon patient well-being and common accompanying facility features that can be identified with data science. Staffing levels matter at nursing facilities, and the positive and negative effects of raising and lowering those levels should be kept in mind when evaluating facility quality.

Some limitations to this study include the nature of tree models and focusing on only one type, Light GBMs, for feature importance analysis. Important features are chosen by tree models based on how much the model learns from the feature, but the model determines its own splits in the decision tree. This process can become complex to the point that an entire other study could be dedicated to examining the optimal splits in the important features, and on trying out many different tree models for feature importance analysis. Another limitation is that there are many more datasets provided by the CMS that could be included in this research, but weren’t included in this study for the purpose of slightly limiting the scope. Counterintuitive findings such as low staff turnover rates for facilities that lowered staffing over time could be partly explained by having fewer positions to fill, but could also be bolstered by including more data in the model from throughout the other CMS datasets. Quality measurements focused on patient health outcomes can also have obfuscating results when short-stay and long-stay patients are both included in the data for a facility, as they were for many facilities in this study. Adding more granular data with additional research could help with this.

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