Exploring Changes in Nursing Facility Staffing Level Using Data Science

Sandeep Borwal

Souleymane Diawara

Amarnath Kommineni

Andrea Vukorepa

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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.

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 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 complicated 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 are affected 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. Staffing levels are also 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. 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](https://data.cms.gov/provider-data/dataset/djen-97ju) 
  + “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](https://data.cms.gov/provider-data/dataset/ijh5-nb2v) 
  + “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](https://data.cms.gov/provider-data/dataset/r5ix-sfxw) 
  + “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](https://data.cms.gov/provider-data/dataset/4pq5-n9py) 
  + “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, -0.7 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. These were added in an attempt to give a model as much information as possible. Features 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, and to be less prone to over-fitting. 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, 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 package 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 -0.7. This results in a dataset where facilities that had a magnitude of change in staffing levels of less than 0.7 – 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.

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

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.

A graph of a training fit perc

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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 fairly well to the data, but tests significantly poorly on correctly identifying facilities with lower staffing levels. This is our first indicator that the way we define the Lower\_Staffing dependent variable is important. With a cutoff of 0, facilities that only changed their staffing levels a little compared to their peers are likely too similar on either side of the 0 cutoff.

Nevertheless, 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 quality rating, staff turnover, patients-to-beds ratio, and others were informative.

A white sheet with black and blue lines

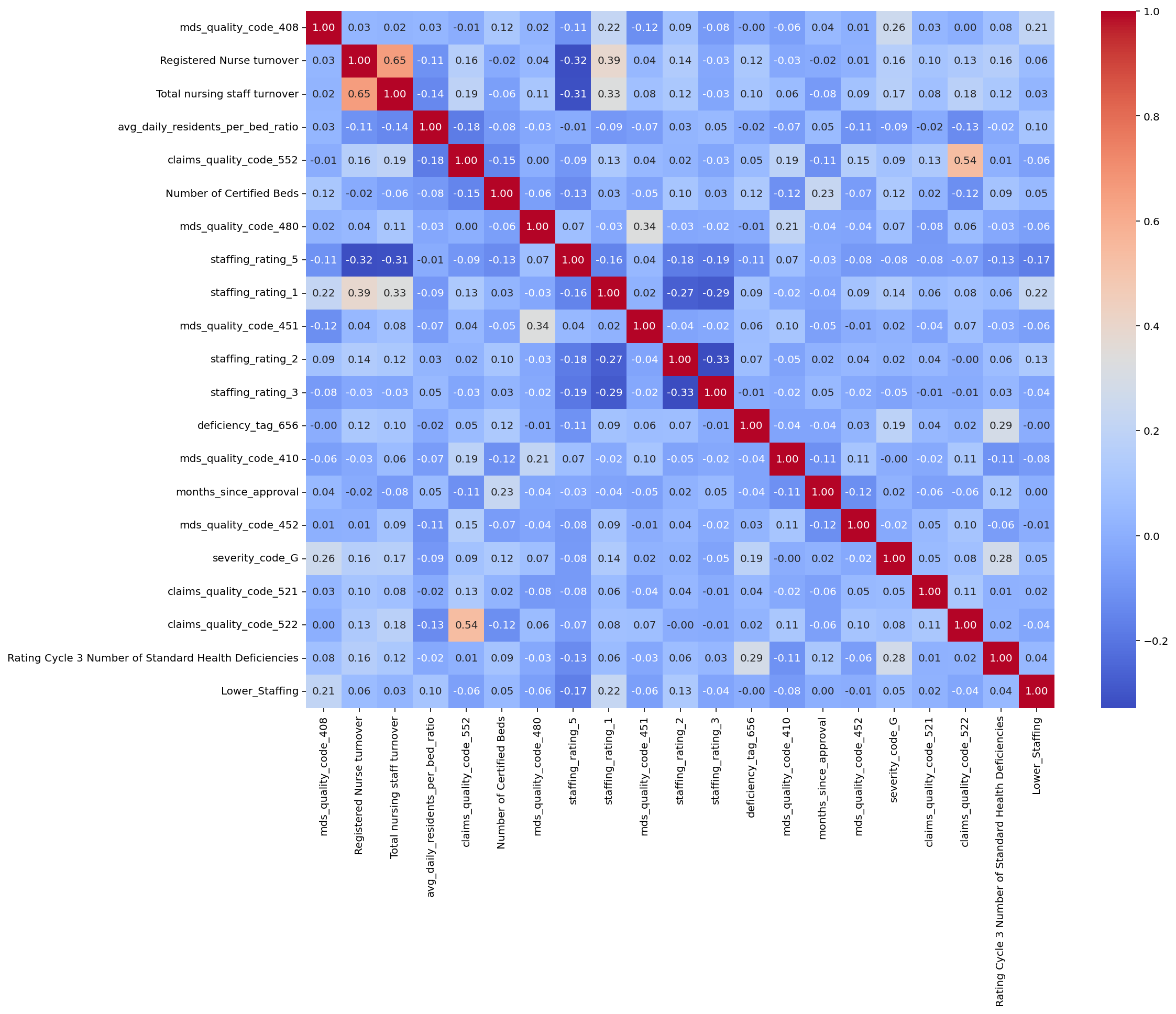
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The Shapley graph gives us similar results, but also shows whether high values per independent variable (red) or low values (blue) increase the likelihood of lower staffing (points to the right) or decrease the likelihood (points to the left).

A screen shot of a chart

AI-generated content may be incorrect.

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:



Many of the staffing, turnover, and rating-related variables are not egregiously correlated. However, logic tells us that behind the curtain, they feed one another.

So when we cull obviously correlated variables, we get a clearer picture of the independent variables that don’t obviously use staffing in their own calculations:

A screen shot of a graph

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An MDS dataset quality code, the percentage of residents who developed symptoms of depression during a long-term stay, is now most highly associated with reduced staffing levels.

However, the model is less performant:

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Now to clarify the analysis, we refine our target variable and which facilities we include in the dataset.

So lastly, when we change our staffing level cutoff to -0.7, we see a stronger and more “predictive” model with similar features persisting in the feature selection visualizations:

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A screenshot of a graph

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# Discussion

While it comes as no surprise that independent variables that use staffing in their calculations help the baseline model to identify facilities that lowered their staffing, there are still some notable insights to identify here.

Firstly, the concept of Lower\_Staffing 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. 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, suggesting tighter accommodations for residents.

Once we strip away closely-associated staffing variables, we see that actual patient health outcomes dominant the most important features, immediately suggesting that staffing levels are closely associated with a facility’s affect on patient well-being. Long-term patients are more likely to develop symptoms of depression in facilities that lowered staffing levels. Non-profit facilities are more closely associated with facilities that actually raised their staffing levels over time.

# Conclusion

Conclusion

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