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Facilitating Focused Process Improvement Efforts in Home Health Agencies to Improve Utilization Outcomes Effectively and Efficiently

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Abstract

The aim of this study was to identify a smaller set of clinical practices most associated with the utilization outcomes of the home health agencies. A secondary data analysis approach was adopted using the publicly accessible Home Health Compare repository as the main data source; the control variables such as rurality, agency size, and median income levels were obtained from other public data repositories. Checking for fall risks and starting care in a timely manner were most associated with hospital readmissions. These two practices and treating patients for pain are most associated with the emergency room visit rates. The results provide additional guidance to home health agencies in their prioritized and focused performance improvement initiatives to improve their utilization outcomes.

Keywords

home care, home health agencies, quality of care, process measures, utilization outcomes, tree-based models

Introduction

In the United States, the utilization outcomes, particularly hospital admissions and emergency room (ER) visits, have become a subject of growing interest in recent years due to the concerns about the projected increase in health care costs.[1-3] Home health care, that is, episodic and intermittent post–acute care services provided to homebound patients in home settings,[4-6] is an important component of the patient-centered continuum of care.[4-6] Quality home care can help improve the utilization outcomes.[7,8] Serving mostly elderly patients, home care services include skilled nursing care, physical therapy, occupational therapy, speech therapy, medical social services, or assistance from a home aide.[9] Given the projected increase in the size of the elderly population in the United States,[10] it becomes critical to monitor and improve the utilization outcomes for home care patients.

The Centers for Medicare and Medicaid (CMS) is the largest payer for home care in the United States.[11] CMS reports the episodic rates of hospital admissions and nonadmitted ER visits for the Medicare-reimbursed home health agencies (HHAs). Since 2016, CMS has implemented a value-based purchasing (VBP) program for home care starting with nine states[12]: Massachusetts, Maryland, North Carolina, Florida, Washington, Arizona, Iowa, Nebraska, and Tennessee. This VBP program involves both penalties and rewards. There are payment reductions for poor performance judged according to certain standards of quality measures, whereas the HHAs outperforming those standards receive financial rewards.[12] Among others, the utilization outcome measures are viewed particularly important by CMS because they are directly tied to health care costs. Moving forward, improving the utilization outcomes becomes vital for HHAs that would like to demonstrate high performance or, at least, achievement to avoid the CMS penalties in the form of payment reductions.

As clinical processes of HHAs improve, their monitored utilization outcomes for home care patients should improve as well.[13-15] Process improvement, however, typically demands a considerable investment of valuable organizational resources.[16] Unfortunately, HHAs often operate with limited financial and human resources.[17,18] Therefore, HHAs need to apply focused and prioritized process improvement efforts to improve their utilization outcomes both effectively and efficiently. So far, as one recent review emphasized, there has been a scarcity of evidence from empirically sound research studies, which can inform HHAs in their initiatives to improve utilization outcomes.[19]

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Table 1. Variable Names Used in Tree-Based Modeling.

Variable type	Variable name
Agency characteristics	Agency Size, RUCA, Median Income, Nursing Servc, Physical Therapy Serv, Occupational Therapy Serv, Speech Pathology Serv, Medical Social Serv
Process measures	Taught Patients Drugs, Check Falling Risk, Check Depression, Diabetes Foot care, Check Pain, Treated Pain, Timely Manner, Treated Heart Failure, Doctor-Ordered Action Prevent Pressure Sores, Treatment Included Prevent Pressure Sores, Check Risk Developing Pressure Sores
Utilization outcome measures	To Be Admitted, Urgent Unplanned Care ER Not Admitted

Note. The two utilization outcome measures served as response variables in two separate models. All of the process measures and agency characteristics were used as predictor variables in modeling. Longer descriptions for the variable names can be seen in the appendix. RUCA = Rural-Urban Commuting Area; ER = emergency room.

To facilitate such focused and prioritized efforts of HHAs, this research study followed a data analytics approach by using data from a set of disparate public databases. Consequently, a smaller set of clinical practices most associated with the home care utilization outcomes were identified. Due to the use of public databases, this research study is reproducible and its results are verifiable by other researchers, which can also be a positive contribution to the scientific advancement of the field. This article provides a detailed description of the methods and results to facilitate such reproducible studies. (A poster presenting the preliminary findings from this study won the outstanding research poster award at the Summer Institute for Nursing Informatics conference.[20])

Methods

Data Collection

Medicare Home Health Compare (MHHC)[21] 2014 database served as the population data for the study. MHHC data are at the HHA level; that is, there is one record for each one of the 12,255 Medicare-reimbursed HHAs in the United States. Each HHA represented in the data set holds a unique CMS Provider ID.

To start with, MHHC data include certain useful agency information such as provider ID, address with a zip code, and whether certain types of home care services (e.g., occupational therapy) are provided or not. For each HHA, MHHC data also include a set of process measures representing the rate of adherence with home care clinical practices. For example, the measure *TaughtPatientsDrugs* for an HHA shows how often its home care clinicians taught patients about drugs; *CheckFallingRisk* shows how often home care clinicians checked for fall risks at home. Before making data public at the MHHC database, CMS aggregates process data to HHA level from the patient-level clinical assessments reported by HHAs as a part of the reimbursement requirements. CMS also makes the utilization outcome measures, the rates of hospital admissions and ER visits without admissions, available at the HHA level. These measures are risk-adjusted using patient-level risk factors including patient's prior care setting, age and sex interactions, Medicare enrollment status, and other interaction terms such as having heart failure and chronic obstructive pulmonary disease.

In addition to the MHHC data, the study incorporated relevant data from other sources. A number of our colleagues in HHAs pointed out that some agency characteristics such as the rurality and the socioeconomic status of the areas served as well as the agency size could also be associated with the home care utilization outcomes. Some earlier empirical evidence also supports this view.[22] Therefore, we included agency characteristics data available both within and outside of the MHHC database for control purposes. Three surrogate measures were obtained from other public data sources and used as control variables to avoid potential confounding effects in the analysis: (1) Rural-Urban Commuting Area (RUCA) codes[23] database hosted by the University of Washington provided levels of rurality. Using the suggested Categorization Scheme A,[24] RUCA was coded as a categorical variable taking values from level 1 to 4, which correspond to urban, rural, very rural, and extremely rural, respectively. (2) Median Income data were obtained from the Population Studies Center at the University of Michigan.[25] RUCA and Median Income were merged with the rest of the data by using HHA zip code. (3) As a proxy for agency size, HHAs' annual visit counts were obtained from CMS Healthcare Cost Report Information System (HCRIS) database[26] and merged with the data by using Provider ID.

Analysis

Consistent with the level of the publicly available data collected, the analysis was conducted at the HHA level where each HHA record constituted an observation. The variables used in the statistical models are shown in Table 1. Each of the two utilization outcome variables in Table 1 was used as a response (outcome) variable separately. All of the rest of the variables were used as predictors in each model.

Regression trees[27,28] were developed by using the rpart package[29] in the statistical environment, R.[30] As we had population data, tree-based modeling was used to describe the relationships between the response and predictors.

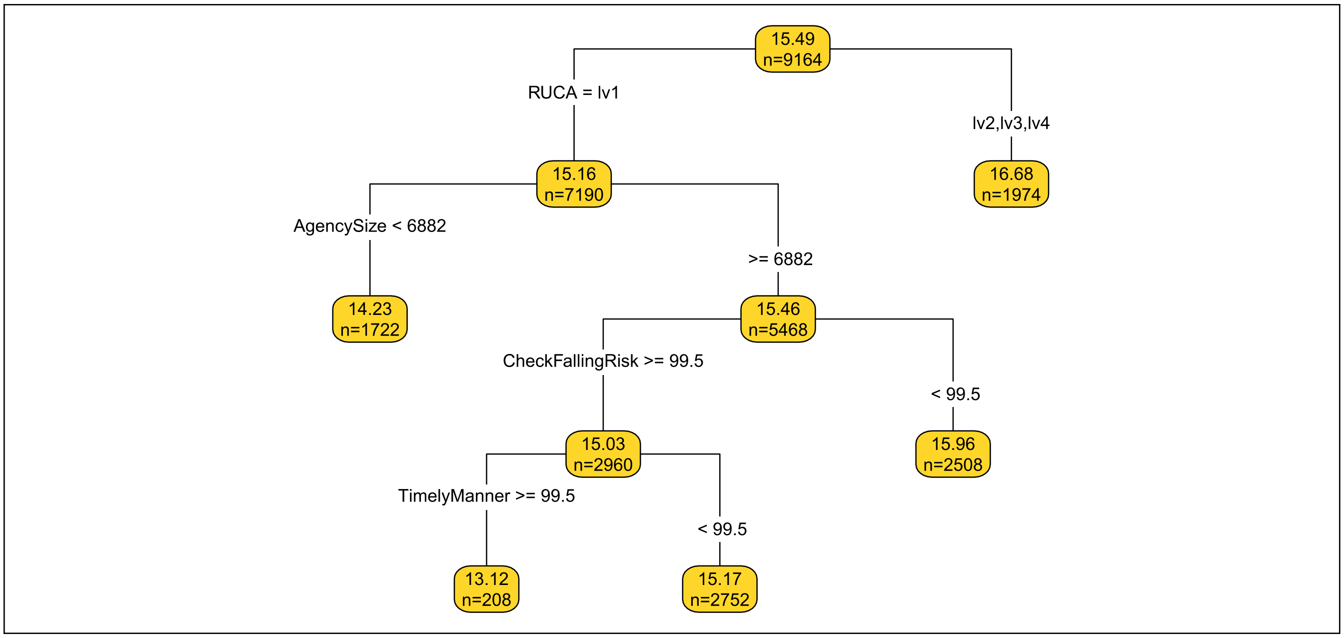

Figure 1. Regression tree for hospital admission rates: In each node, the mean value for the hospital admission rates and the number of HHAs are shown.
Note. HHAs = home health agencies; RUCA = Rural-Urban Commuting Area.

Tree-based models can accommodate nonlinear relationships. Also, they are easy to interpret and understand because variable space is split in such a way that observations with similar characteristics come together in nodes.

The process for creating a regression tree starts with creating a root node which includes all of the observations in a data set. The root node is recursively partitioned into two to create two child nodes. The recursive partitioning results in a structure that looks like an upside-down tree (e.g., see Figures 1 and 2). For each split used for partitioning, the best predictor-threshold pair is selected among all other possible pairs such that the maximum variance reduction in the response variable is obtained. Therefore, the top splits are considered to be the most important splits. Splitting can be stopped when there is no significant gain in the variance reduction or when a minimum of number of observations in the leaf nodes is reached according to a set threshold. The tree is decided by taking the tree size that corresponds to the complexity parameter that results in minimum cross-validated error (10-fold cross-validation is used). This process, in our case, is applied for each of the two utilization outcomes separately by considering all of the predictors seen in Table 1. Variable importance was measured by using the rpart package as well. For each predictor variable included in regression tree modeling, a variable importance score is calculated as a measure of total variance reduction contributed by that predictor across all splits, either as a primary or surrogate splitter. Surrogate splitter is a predictor used when the primary splitter has missing values for certain observations. The surrogate splits used in rpart package is an effective way of dealing with missing data in predictors.[31] For some observations, the response variables were missing because CMS did not report utilization outcomes for HHAs with less than 20 patients. Consequently, 9,164 observations were used in creating the tree-based models.

Results

Figures 1 and 2 show the regression trees developed to model the hospital admission and ER visit rates, respectively. In each node of a tree, the mean value for the response variable and the number of observations are shown. For each split, there is a condition with a pair of predictor and threshold values on the left branch categorizing the observations to the left child; the observations which do not meet that condition go to the right child. As a result of this recursive process, HHAs with similar characteristics, process measures, and utilization outcomes are clustered together in the resulting models.

Interestingly, RUCA, a variable included to control for rurality, reduced the utilization variance most in both models shown in Figures 1 and 2. Both utilization outcomes were worse for HHAs serving in rural areas with the RUCA levels of 2, 3, and 4. Median Income became relevant only when RUCA was not included but dropped out of the models, otherwise. Service variables did not appear in our models. Agency Size seemed to have an effect for urban HHAs in both models, with larger HHAs having higher rates of utilization. The results show that some proxy

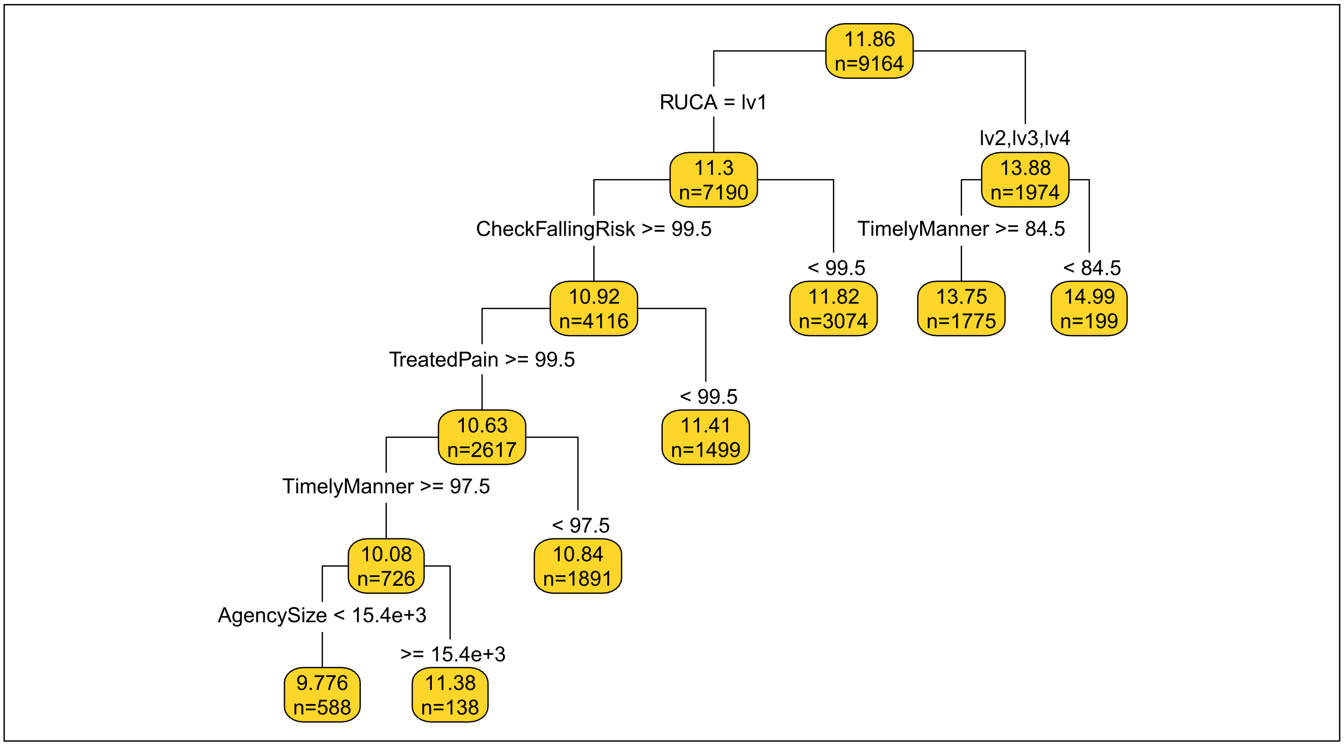

Figure 2. Regression tree for nonadmitted emergency room visit rates: In each node, the mean value for the rate of unplanned ER visits not resulting in hospital admissions and the number of HHAs are shown.
Note. ER = emergency room; HHAs = home health agencies; RUCA = Rural-Urban Commuting Area.

measures we used for agency characteristics such as agency size, rurality, and social determinants of health in areas served by the agency are highly associated with the utilization outcomes. In fact, not including them in the models would obstruct the relationships between the process measures and utilization outcomes, detracting from the quality of our results.

Hospital Admissions

In Figure 1, it can be seen that the average hospital admission rate for urban agencies is 1.52% lower than rural agencies. The rural HHAs, whose number was 1974, had an average rate of 16.68%, and there was no further statistically useful split by using any of the predictors for the rural agencies. Among the 7,190 urban HHAs, those with an annual visit count of less than 6882 had an average rate of 14.23%; however, 5,468 HHAs with a larger size had an average rate of 15.46%. Two process measures become relevant for larger agencies with a size of 6682 or above: checking for fall risks and starting care in a timely manner.

Among the larger urban HHAs, 2,960 of those who checked for falling risks 100% of the time achieved a 0.93% lower average admission rate compared with 2508 HHAs who did not. Furthermore, a cluster of 208 larger urban HHAs that both checked for fall risks and started care in a timely manner 100% of the time had the lowest average rate, 13.12%, in the model. This lowest rate, within similar HHAs (larger urban), is (1) 2.05% lower than the rate for those who always check for fall risks but not consistently start the care in a timely manner, and (2) 2.85% lower than those who do not always check for fall risks. These results show an association between adherence with two important clinical practices and better outcomes in terms of hospital admissions.

ER Visits

In Figure 2, it can be seen that the rural HHAs have an average ER visit rate of 13.88%, which is 2.58% higher than urban HHAs. The model also shows that, in rural areas, timely start of home care is a highly important practice associated with the ER visits. There are 199 rural HHAs whose adherence with starting care in a timely manner is less than 84.5% of the times. This cluster, represented by the right-most node, has the highest rate in the model, almost 15%.

Among the urban agencies, checking for fall risks consistently, treating patients for pain, and starting care in a timely manner appear in the top splits. The urban HHAs with higher adherence with these three practices (n = 726) have an

Table 2. Variable Importance Scores for Variables in the Models: (a) Hospital Admission Rates and (b) ER Visit Rates.

(a) Hospital Admission Rates model	(b) ER Visit Rates model
RUCA: 41	RUCA: 68
Agency Size: 20	Check Falling Risk: 9
Check Falling Risk: 12	Treated Pain: 5
Timely Manner: 12	Timely Manner: 4
	Agency Size: 2

Note. ER = emergency room; HHAs = home health agencies.

average rate of 10.08%. For those agencies, Agency Size appears to play a role. There are 138 HHAs with more than 15,400 annual visits with an average rate of 11.38%, whereas 588 HHAs making less visits have an average rate of 9.78%.

The model in Figure 2 shows an association between adherence with clinical practices and better outcomes in terms of ER visits. The two measures, checking falling risks and starting care in a timely manner, are relevant, similar to the case with the hospital admissions. However, when ER visits considered, treating patients for pain also becomes relevant.

Variable Importance

The variable importance scores for the predictors in the models as obtained from rpart package are summarized in Table 2. It can be seen that RUCA has the highest score in both models.

RUCA is followed by agency size for hospital admission rates. The two clinical variables, checking for fall risks and starting care in a timely manner, receive an equal score of 12.

RUCA's relative importance is even higher in the ER Visit Rates model. Checking for fall risks, treating patients for pain, and starting care in a timely manner received the variable importance scores of 9, 5, and 4, respectively. The clinical variables are followed by Agency Size with a score of 2.

Discussion

Along with the VBP pilot program, CMS has recently finalized a set of rules to improve quality of care and patient rights in home care. These rules serve as the Condition of Participation (CoP) in Medicare.[32] One rule specifically requires every HHA to implement a data-driven Quality and Performance Improvement (QAPI) program that continually evaluates and improves agency care for all patients at all times. Rather than being prescriptive, CMS explicitly acknowledges the difficulty of providing specific instructions to HHAs about implementing QAPI programs. While requesting QAPI initiatives from every HHA could be ideal, there are also realities associated with limited budgets. Most HHAs are highly occupied with running their daily clinical and administrative functions and surviving as a viable business in the near future.

The results from this study should be immediately useful to HHAs in their focused and prioritized process improvement efforts targeting to improve utilization outcomes. The results provide a prioritized list of clinical practices most associated with utilization outcomes. It turns out that checking for fall risks is the practice most associated with the utilization outcomes. This finding is consistent with the CMS-reported data about potentially avoidable events (PAEs) in home care, which highlights the ER visits due to falls as the most prevalent PAE.[33] Another important clinical process is starting care in a timely manner; timeliness appears in both models, but it is more important for hospital admissions. HHAs which did not consistently provide timely care had higher rates of hospital admissions. In addition, the results suggest that treating patients for pain and starting care in a timely manner can possibly lower the ER visit rates.

The results also indicate that nonclinical variables were more associated with utilization outcomes, which indicates that the feedback we received from our colleagues was on target. It is, in fact, important and well-worth the effort to control for the nonclinical variables in the research study, which improved the quality of our results. In terms of variable importance, RUCA has the highest scores in Table 2. Numerous effects associated with rurality could be at play. Perhaps HHAs in rural areas have limited budgets for process and quality improvement initiatives. Alternatively, lower levels of income, education, and health literacy levels in rural areas, reported in some of the earlier studies,[34-37] might be affecting the home care utilization outcomes. In addition, due to a lack of adequate, accessible, and timely primary and secondary care, rural patients may end up visiting ERs or get admitted to hospitals more easily.[38] Such factors can directly increase hospitalization and ER visit chances for rural home care patients. Based on these findings, policy makers may consider providing more support to rural HHAs to improve the utilization outcomes.

Limitations

As usual, there are a number of limitations due to the nature of this empirical study. For very small HHAs, specifically for the HHAs making less than 20 annual visits, CMS does not provide the utilization outcomes which results in a missing response variable for those HHAs. When the response variable was missing for an observation, that observation had be excluded in tree-based modeling. Still, the models created in this study had sufficient number of observations to draw valid conclusions.

Two variables about checking for vaccinations, flu and pneumococcal, were excluded from analysis. These two practices are selectively applied to severe patients. However, the analysis conducted was at the HHA level and we do not have severity data at the HHA level; thus, these two variables had to be excluded from the analysis to prevent confounding effects.

In this study, tree-based modeling was used mainly to characterize HHAs according to a set of process measures and utilization outcomes, not for predicting the utilization outcomes for individual HHAs. The latter requires models that explain the variance in the utilization outcomes more substantially. Finally, cause-effect relationships should not be inferred from the results of secondary data analysis studies; our results should be interpreted and used along with the knowledge and data related to the specific context of an HHA.

Conclusions

Rurality and agency size play an important role in the utilization outcomes. Checking for fall risks, starting care in a timely manner, and treating patients for pain are the most important clinical practices associated with the utilization outcomes of HHAs. The results should help HHAs apply focused and prioritized process improvement efforts to improve their utilization outcomes effectively and efficiently. The results can also serve policy makers who make decisions to reduce disparities and improve quality in home care. MHHC infrastructure proves to be useful and holds potentials for supporting reproducible research in the future.

Appendix

Descriptions for the Variables Considered in the Study.

Variable name	Variable description
Agency Size[a]	Annual Visit Count used as proxy measure for agency size
RUCA[b]	Rural-Urban Commuting Area level—Categorization Scheme A[24] used as proxy measure for rurality
Median Income[c]	Median Household Income used as proxy measure for socioeconomic status
Nursing Servc	Offers nursing care services (Yes/No)
Physical Therapy Serv	Offers physical therapy services (Yes/No)
Occupational Therapy Serv	Offers occupational therapy services (Yes/No)
Speech Pathology Serv	Offers speech pathology services (Yes/No)
Medical Social Serv	Offers medical social services (Yes/No)
Taught Patients Drugs	How often the home health team taught patients (or their family caregivers) about their drugs
Check Falling Risk	How often the home health team checked patients' risk of falling
Check Depression	How often the home health team checked patients for depression
Check Flu Shot Current Season	How often the home health team determined whether patients received a flu shot for the current flu season
Determined Pneumococcal Vaccine	How often the home health team determined whether their patients received a pneumococcal vaccine
Diabetes Footcare	With diabetes, how often the home health team got doctor's orders, gave foot care, and taught patients about foot care
Timely Manner	How often the home health team began their patients' care in a timely manner
Check Pain	How often the home health team checked patients for pain
Treated Pain	How often the home health team treated their patients' pain
Treated Heart Failure	How often the home health team treated heart failure (weakening of the heart) patients' symptoms
Doctor-Ordered Action Prevent Pressure Sores	How often the home health team took doctor-ordered action to prevent pressure sores
Treatment Included Prevent Pressure Sores	How often the home health team included treatments to prevent pressure sores
Check Risk Developing Pressure Sores	How often the home health team checked patients for the risk of developing pressure sores
To Be Admitted	How often home health patients had to be admitted to the hospital
Urgent Unplanned Care ER Not Admitted	How often patients receiving home health care needed urgent, unplanned care in the ER without being admitted

Note. ER = emergency room; CMS = Centers for Medicare and Medicaid Services.
Data sources: [a]CMS Healthcare Cost Report Information System (HCRIS) database,[26] [b]University of Washington,[23,24] and [c]Population Studies Center at the University of Michigan.[25] Unless marked by superscript, variables come from Medicare Home Health Compare database.[21,39]

Authors' Note

This research primarily used a secondary-data analysis approach by leveraging publicly available databases about home health agencies. Therefore, the research did not meet the definition of human-subjects research.
Dr. Dari Alhuwail is now affiliated with University of Kuwait.

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Declaration of Conflicting Interests

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