RESEARCH ARTICLE

Informing a home time measure reflective of quality of life: A data driven investigation of time frames and settings of health care utilization

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Abstract

Objective: To evaluate short- and long-term measures of health care utilization—days in the emergency department (ED), inpatient (IP) care, and rehabilitation in a post-acute care (PAC) facility—to understand how home time (i.e., days alive and not in an acute or PAC setting) corresponds to quality of life (QoL).

Data Sources: Survey data on community-residing veterans combined with multi-payer administrative data on health care utilization.

Study Design: VA or Medicare health care utilization, quantified as days of care received in the ED, IP, and PAC in the 6 and 18 months preceding survey completion, were used to predict seven QoL-related measures collected during the survey. Elastic net machine learning was used to construct models, with resulting regression coefficients used to develop a weighted utilization variable. This was then compared with an unweighted count of days with any utilization.

Principal Findings: In the short term (6 months), PAC utilization emerged as the most salient predictor of decreased QoL, whereas no setting predominated in the long term (18 months). Results varied by outcome and time frame, with some protective effects observed. In the 6-month time frame, each weighted day of utilization was associated with a greater likelihood of activity of daily living deficits (0.5%, 95% CI: 0.1%–0.9%), as was the case with each unweighted day of utilization (0.6%, 95% CI: 0.3%–1.0%). The same was true in the 18-month time frame (for both weighted and unweighted, 0.1%, 95% CI: 0.0%–0.3%). Days of utilization were also significantly associated with greater rates of instrumental ADL deficits and fair/poor health, albeit

not consistently across all models. Neither measure outperformed the other in direct comparisons.

Conclusions: These results can provide guidance on how to measure home time using multipayer administrative data. While no setting predominated in the long term, all settings were significant predictors of QoL measures.

KEYWORDS

days alive and not at home, health care utilization, home time, machine learning, patient-centered outcomes, quality of life, veterans

What is known on this topic

- Home time measures have gained appeal in evaluating outcomes where more time at home and less in health care settings has been consistent with higher quality of life (QoL) and quality of care (QoC).
- No prior work has sought to quantitatively demonstrate whether and how different types of health care settings matter in terms of a home time measure and QoL.

What this study adds

- This study advances the science of home time measures by exploring how home time measures associate with QoL, which health care settings to include, and which time frames of utilization are important.
- Such advances can inform value-based payment initiatives that equate organizational performance and QoC with more home time.

1 | INTRODUCTION

Older adults overwhelmingly prefer to remain at home as they age.[1-5] Thus, remaining at home generally reflects higher quality of life (QoL) because it is consistent with older adults' life goals.[6] In the context of health events that result in older adults being away from home, researchers have used a measure of time alive and away from home (the converse of "home time") as a marker of both QoL[7] and quality of care (QoC)[8] Home time measures have gained appeal in evaluating outcomes for multiple patient populations, including post-surgery,[9,10] post-intervention,[11] and in the last 6 months of life for terminally ill patients.[12,13] More time at home and less in health care settings such as hospitals and rehabilitation facilities has been assumed to be consistent with higher QoL and QoC. Nevertheless, there are gaps in our understanding of these measures' utility: Even though we have asserted that home time relates to QoL, research directly associating home time with person-centered outcomes has been limited.[7,14-16] Moreover, at present, no prior work has sought to quantitatively demonstrate whether and the extent to which different types of health care settings matter in terms of home time, nor is it clear to what degree time frame of health care utilization is important.

To advance the science of home time measures, researchers need to quantify how more days away from home and in different health care settings detract from QoL-related outcomes, such as self-reported health, functional impairment, depressive symptoms, and pain. In this paper, we explore how well measures of home time correspond with components of QoL, with the goals of (1) establishing

which health care settings we should include in the definition of home time, (2) determining which time frames of health care utilization are most reflective of QoL, and (3) assessing how a weighted measure of home time compares to a standard measure of home time (i.e., an unweighted measure of summed utilization) at 6 and 18 months. To do so, we examined days in inpatient (IP) hospitalizations; post-acute care (PAC), including rehabilitation, skilled nursing, and assisted living; and emergency department (ED) settings as predictors of QoL, with the goal of establishing whether care in one setting is more greatly associated with patient QoL than care in other settings. The secondary goal was to establish whether there is a quantifiable relationship between cumulative days at home and QoL to determine the person-centeredness of home time measures.

IP, PAC, and ED settings were selected because clinical studies document negative impacts of time spent in acute settings, including functional decline, delirium, and hospital-acquired infections, and PAC settings signify loss of control to patients.[6-8] We also examined two different time frames of health care utilization—6 months and 18 months—to determine whether short-term utilization or long-term utilization is most closely associated with patient QoL. We then used the results of these models to produce weighted measures of utilization at both 6 and 18 months, which we compared to corresponding unweighted raw counts of cumulative days in any of the three settings (ED, PAC, and IP), with the goal of assessing a weighted utilization variable as a proof of concept. Ultimately, this paper can serve as an important template for creating a home time measure for older adults that is both person-centered and data driven as well as one that can be developed on large populations using claims data.

2 | METHODS

2.1 | Study cohort and patient-reported outcomes

We identified a cohort of 570 veterans from an existing national comparative effectiveness study (GeriPACT),[17] which enrolled community-dwelling veterans aged 65 years and older in a national VA-funded geriatric patient-centered medical home model study.* From 2018 to 2019, those veterans participated in a telephone-based survey, completing measures on self-reported health and well-being, depressive symptoms, functional disability, and social support. Details on the eligibility and recruitment of those participating in the survey have been previously published.[17] These patient-reported outcomes, seven in all, represent important components of overall QoL.[17] Additionally, self-reported health has been mapped directly to health utility measures, which reflect global health-related QoL.[18–21] For the present study, we used administrative claims data to capture health care utilization by these veterans in the months preceding completion of the survey. This study was approved as exempt research by the Institutional Review Board of the Durham VA Health Care System.

2.2 | Health care utilization

To examine home time associations with patient-reported outcomes, utilization prior to veterans' participation in the telephone-based surveys was defined by the number of days in IP (days in an observation, medical, or surgical unit in a hospital setting), PAC (facility-based short-term nursing home days and IP rehabilitation days), and ED (ED visits where one or multiple visits on the same day count as 1 day) settings using administrative claims data from VA health records (Corporate Data Warehouse and Observational Medical Outcomes Partnership data sources), VA-purchased community care (Fee Basis and Program Integrity Tool data sources), and Centers for Medicare and Medicaid Services (CMS) (Medicare Provider and Analysis Review, Outpatient, and Minimum Data Set files). The CMS files provide utilization for fee-for-service and Medicare Advantage beneficiaries for IP and PAC but do not capture ED visits for veterans on Medicare Advantage. Because Medicare is the primary payer of acute and PAC services for dual beneficiaries (veterans also enrolled in Medicaid as well as Medicare), we captured both Medicare- and Medicaid-financed utilization for nearly all study participants (98.8% of veterans were enrolled in Medicare for at least 1 month during the 18-month utilization window). Respite stays (IP or outpatient), which are a VA-covered service that provides care for a short time when family caregivers need a break to run errands or travel without their veteran care recipient, were not included in the present analyses, because this care is often planned and may be consistent with

higher QoL. IP hospice care was also not included because our sample was drawn from noninstitutionalized veterans not receiving hospice or palliative care who were healthy enough to consent to participate in the parent study.[17] Additionally, it is not clear whether this type of utilization represents a lower QoL "day," which is dependent on preferences and alternatives that may be difficult to determine via administrative claims.

2.3 | Measures

The primary outcomes of our current study were seven patient-reported measures that reflect various components of QoL. Measures of health and well-being were drawn from the Patient-Reported Outcomes Measurement System 29-item Health Profile (PROMIS-29).[22,23] The following PROMIS-29 measures were selected for the present study: depression in the last 7 days, pain in the last 7 days, sleep dysfunction in the last 7 days, and social support (i.e., social activities and roles). Because of challenging distributional properties, these measures were dichotomized prior to modeling using established cutoffs (https://www.healthmeasures.net/score-and-interpret/interpret-scores/promis/promis-score-cut-points; Accessed March 22, 2022) for depression and pain (i.e., moderate and severe vs. within normal limits and mild), sleep dysfunction (i.e., mild, moderate, and severe vs. within normal limits), and social support (i.e., very low and low vs. average to very high). Functional status, defined as being unable to perform a basic activity of daily living (ADL), either at all or without the help of another person,[24] was also obtained from the patient survey, as there is no reliable way to ascertain ADL dependency from the medical record or administrative data. ADL functional status was modeled using ADL deficits and instrumental ADL (IADL) deficits. Both ADL and IADL deficits were dichotomized at three or greater (out of seven surveyed) versus less than three.[25] Self-reported health[26] was captured using a five-point scale (ranging from 1 *excellent* to 5 *poor*), with model cutoffs at excellent/very good/good versus fair/poor.

2.4 | Model covariates

The following covariates were included in each model of the QoL outcomes: (a) predisposing factors collected from the patient at the time of the baseline survey, including age (categorized as 65–69 years, 70–79, 80–89, and 90 or older), gender, race, Hispanic/Latino(a) ethnicity, and marital status; (b) urban/rural status from VA health record data collected at the beginning of the utilization window (18 months prior to baseline survey); and (c) medical need factors collected at the start of the 18-month utilization window, including dementia diagnosis from VA health records and Nosos score.[27] Nosos is a chronic health condition risk score using diagnostic codes and pharmacy information that measure expected health care costs compared with the average patient, with a risk score greater than one representing a higher-than-expected cost for the patient.

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*The GeriPACT study initially enrolled 570 patients but ultimately excluded two: one patient who had spent the entire exposure period in a nursing home but then returned home prior to the baseline interview and the corresponding matched patient. These two patients were retained in the present study.

2.5 | Data analysis

To determine how varying definitions of home time, operationalized via the three aforementioned types of utilization, were associated with each of the seven QoL measures, we used elastic net logistic regression and k-fold cross-validation.[28] This machine learning approach was chosen given that it is robust to collinearity, which we anticipated would be high among the utilization variables. Briefly, elastic net regularization features a combination of LASSO regularization, whereby the number of variables in the model is penalized, and ridge regularization, whereby the size of the coefficients for each variable in the model is penalized. These penalties deter overfitting, ensuring that the resulting model coefficients are generalizable across samples from the same population, at the cost of slight bias. In other words, elastic net coefficients vary less from sample to sample than those derived from unpenalized modeling techniques, but they typically are consistently smaller than what would be found in the overall population. Given this bias, standard errors and confidence intervals are not reported for corresponding model coefficients. Additionally, some covariates may drop out of the model (i.e., be equal to zero) if determined via cross-validation to be uninfluential in predicting the outcome at hand.

A separate model was fit for each of the seven QoL-related measures that included the primary utilization variables of interest as well as adjustment for the model covariates described above. Categorical variables were dummy-coded, and continuous/count variables, including the three utilization variables, were z-scored, as is required for penalized regression. To deter under- and overfitting of the models, we randomly partitioned the sample into training and test sets along a 70/30 split. The training set was used to develop and tune the models, and the test set was used to evaluate the models' performance on heretofore unseen data. Repeated k-fold, specifically fivefold, cross-validation was applied to the training set to derive optimal values of the elastic net hyperparameters corresponding to the size and balance (lambda and alpha, respectively) of the LASSO and ridge penalties. Hyperparameters were optimized via grid search on Cohen's kappa, with values of 0.00–0.09 reflecting little to no agreement between predictions and observations, 0.10–0.20 slight agreement, and 0.21–0.40 moderate agreement. Negative kappas reflect disagreement. Each fivefold cross-validation was repeated 10 times, with the data randomly shuffled between repetitions. Once the optimal model hyperparameters were determined through the repeated cross-validation process, the model was refit to the full training set with those hyperparameter values fixed. The resulting parameters (i.e., coefficients) were then used to score the test set and generate summary measures of model fit (i.e., Cohen's kappa). The above process was performed twice—once for 6-month utilization and again for 18-month utilization.

Once the 6- and 18-month utilization effects were estimated, we conducted a second set of analyses to examine the utility of a weighted health care utilization variable. Specifically, we transformed the coefficients from the elastic net models to reflect the impact of a single day in each health care setting on all seven QoL outcomes. We then averaged these transformed coefficients to derive weights specific to each type of utilization, which we multiplied by the corresponding raw utilization counts of each type and summed, thus creating a single weighted utilization variable for each veteran. To determine how this weighted utilization variable compared with a raw unweighted count of the number of days spent in any of the ED, IP, and PAC settings, we used unpenalized logistic regression to model the effects of both variables in separate models, using the same covariates used in the previous models, on the seven QoL outcomes. To facilitate interpretation of the weighted variable, we scaled it so that its variance matched that of the corresponding unweighted utilization variable. We then used a two-sided z-test to compare the two resulting effects.[29] This process was performed twice, once for 6-month utilization and again for 18-month utilization.

Missing values, either for outcome or predictor variables, resulted in case-wise deletion. Primary analyses were conducted using R, version 4.1.2. Elastic net logistic regression and repeated k-fold cross-validation were performed using the "glmnet" and "caret" packages, respectively. Estimated marginal effects (EMEs) are reported representing the percent difference in the predicted probability of an outcome level (vs. the reference level) associated with a one-unit change in the predictor variable (in its original, pre-z-scored scale) with baseline outcome probability levels derived from observed rates. Thus, EMEs represent the effect of 1 day of utilization on the increased (or decreased) probability of a negative QoL outcome.

3 | RESULTS

Summary statistics for the GeriPACT cohort are displayed in Table 1. The sample comprised largely of White, non-Hispanic/Latino older adult males. Short- (6-month) and long-term (18-month) health care utilization is summarized in Table 2. A quarter of the sample spent at least 1 day in the ED in the prior 6 months, and more than half did so in the prior 18 months. IP utilization was lower, with around 13% spending at least a day in an IP setting in the previous 6 months and nearly a third spending at least a day in IP care in the previous 18 months. Just over 3% of patients spent at least 1 day in PAC in the prior 6 months, and just over 7% did so in the prior 18 months.

Results from the elastic net logistic regression models of 6-month health care utilization are displayed in Table 3. According to the indices of model fit (Cohen's kappa values) derived from applying the final models to the test set, only three of the models demonstrated at least slight agreement among predicted and observed outcomes: ADL deficits, IADL deficits, and self-reported health. However, in six out of the seven models, PAC utilization emerged as the strongest indicator based on coefficient size. Contrary to expectation, greater IP utilization was associated with decreased rates of poor QoL outcomes in five out of seven models, and greater ED utilization was associated with decreased rates of poor QoL outcomes in four out of the seven models.

Results from the 18-month utilization models are shown in Table 4. As with the 6-month utilization analyses, only three of the 18-month models demonstrated at least slight agreement among

TABLE 1 Cohort characteristics (N = 570).

	n (%)	Mean (SD)	Missing (%)
Female gender	10 (1.8%)		
Hispanic/Latino(a) ethnicity[a]	22 (3.9%)		
Race[b]			
White	457 (80.2%)		
Black	72 (12.6%)		
Other	41 (7.2%)		
Age in years		80.5 (7.0)	
Married or living as married	337 (59.1)		
Rural (vs. urban) status	163 (28.6)		
Nosos prospective score[c]		1.1 (0.9)	7 (1.2%)
Dementia diagnosis	29 (5.1)		
Patient-centered outcomes			
ADL deficits		1.2 (1.6)	
IADL deficits		2.0 (2.2)	
PROMIS depression[d]		49.2 (9.0)	8 (1.4%)
PROMIS pain[d]		55.9 (9.9)	14 (2.5%)
PROMIS sleep[d]		49.1 (9.2)	5 (0.9%)
PROMIS social support[d]		49.8 (10.3)	14 (2.5%)
Self-reported health (5-point scale from 1 = excellent to 5 = poor)		2.9 (1.1)	2 (0.4%)

Note: Missing cases only reported where nonzero.

Abbreviations: ADL, activity of daily living; IADL, instrumental activity of daily living; PROMIS, Patient-Reported Outcomes Measurement System 29-item Health Profile (PROMIS-29); SD, standard deviation.

[a]Three veterans who reported "do not know", refused, or had missing data for Hispanic/Latino(a) ethnicity are categorized as not being of Hispanic/Latino(a) ethnicity for analytical purposes.

[b]Race was categorized into three levels; White race (only racial category selected), Black race (can be only category selected or have additional racial categories selected), Other race (includes those selecting Asian, Native Hawaiian or Alaskan Native, Native American, Other race, multiple race categories selected [except for those who also selected Black race]). One veteran had missing for race and was included in the "Other" race category for analytical purposes.

[c]Nosos scores are centered around 1, where a score of 1 indicates the veteran is expected to have costs that are the national average for VA patients. If a veteran has a score of 1.5, then their expected cost is 1.5 higher than the average VA patient.

[d]The PROMIS scales are standardized T-scores, with means of 50 and standard deviations of 10.

TABLE 2 Summary of health care utilization.

	Patients with ≥1 day of utilization (%)	Days of utilization	
		Mean (SD)	Q1–Q3
6 Months			
ED	145 (25.4%)	0.41 (0.91)	0–1
IP	73 (12.8%)	0.81 (2.86)	0–0
PAC	19 (3.3%)	0.95 (6.60)	0–0
Any	166 (29.1%)	2.04 (8.19)	0–1
18 Months			
ED	320 (56.1%)	1.36 (1.90)	0–2
IP	176 (30.9%)	2.82 (6.92)	0–3
PAC	42 (7.4%)	2.96 (21.16)	0–0
Any	339 (59.5%)	6.70 (23.55)	0–5

Abbreviations: Any, any utilization of ED, IP, or PAC. Multiple types of care (ED, IP, and PAC) can occur on a given day; ED, emergency department; IP, inpatient hospitalization; PAC, post-acute care facility; Q1–Q3, range from first quartile to third quartile; SD, standard deviation.

TABLE 3 Elastic net logistic regression models of health and well-being based on 6-month utilization.

	ADL deficits ≥3 (16.1%)		IADL deficits ≥3 (31.1%)		PROMIS depression Moderate/severe (14.2%)		PROMIS pain Moderate/severe (34.4%)		PROMIS sleep Mild–severe (24.1%)		PROMIS social support Very low/low (17.1%)		Self-reported health Fair/poor (30.1%)	
	Coef.	EME	Coef.	EME	Coef.	EME	Coef.	EME	Coef.	EME	Coef.	EME	Coef.	EME
Intercept	-3.87	-	-1.59	-	-5.43	-	-0.80	-	-2.15	-	-2.24	-	-0.03	-
6-month utilization														
ED	-0.03	-0.4%	-0.04	-1.0%	-0.14	-1.9%	-0.02	-0.6%	0.03	0.3%	0.05	0.8%	0.31	7.3%
IP	0.17	0.8%	0.04	0.3%	-0.35	-1.5%	-0.20	-1.6%	-0.22	-0.6%	-0.12	-0.6%	-0.09	-0.7%
PAC	0.24	0.5%	0.17	0.5%	0.37	0.7%	0.18	0.6%	0.34	0.4%	0.28	0.6%	0.89	2.8%
Female gender[a]	-0.77	-10.4%	0.00	0.0%	2.78	34.0%	-0.54	-12.2%	-0.41	-3.3%	0.59	8.4%	-1.20	-25.3%
Age group[b]														
70–79	1.52	20.6%	0.00	0.0%	0.41	5.0%	0.98	22.1%	0.21	1.7%	0.49	6.9%	0.50	10.4%
80–89	1.85	25.1%	0.19	4.2%	0.47	5.7%	0.48	10.9%	0.00	0.0%	0.28	3.9%	0.15	3.1%
90+	3.31	44.85	1.61	34.4%	0.25	3.1%	0.46	10.4%	0.00	0.0%	0.26	3.6%	0.08	1.7%
Hispanic/Latino(a)[c]	0.88	11.9%	0.21	4.4%	0.10	1.2%	-0.77	-17.3%	0.79	6.3%	0.06	0.8%	0.69	14.4%
Married or living as married[d]	1.12	15.1%	0.59	12.6%	0.37	4.5%	0.33	7.5%	0.00	0.0%	-0.11	-1.6%	0.41	8.6%
Race[e]														
Black	0.55	7.4%	0.12	2.7%	0.00	0.0%	0.44	9.8%	-0.99	-8.0%	0.05	0.7%	0.02	0.4%
Other	0.94	12.8%	0.75	16.0%	1.03	12.5%	1.42	32.0%	0.88	7.1%	1.05	14.9%	0.08	1.7%
Rural status[f]	-0.18	-2.5%	0.00	0.0%	-0.04	-0.4%	-0.31	-7.0%	-0.20	-1.7%	-0.45	-6.3%	-0.27	-5.6%
Nosos prospective score	0.98	14.1%	0.43	9.7%	-0.05	-0.6%	0.47	11.2%	0.00	0.0%	0.36	5.5%	0.37	8.3%
Dementia diagnosis[g]	0.25	34.6%	2.98	63.8%	1.69	20.6%	-0.52	-11.7%	0.00	0.0%	1.38	19.6%	1.18	24.8%
Hyperparameters and model Fit														
Missing n (%)	4 (1.0%)		4 (1.0%)		10 (2.5%)		14 (3.5%)		7 (1.8%)		14 (3.5%)		4 (1.0%)	
Alpha	0.10		0.18		0.43		0.10		0.84		0.51		0.67	
Lambda	0.00		0.03		0.00		0.00		0.00		0.00		0.00	
Cohen's kappa (test set)	0.25		0.16		-0.04		0.08		-0.02		-0.06		0.12	

Note: Model coefficients (coef.) and estimated marginal effects (EMEs) derived from analysis on full training set (*n* = 399). For continuous variables (18-month utilization, Nosos prospective score), EMEs were calculated based on original unstandardized scales. Missing values resulted in case-wise deletion.

Abbreviations: ADL, activity of daily living; ED, emergency department; IADL, instrumental activity of daily living; IP, inpatient hospitalization; PAC, post-acute care facility; PROMIS, Patient-Reported Outcomes Measurement System 29-item Health Profile (PROMIS-29).

[a]Male participants represent reference group.

[b]Participants 65–69 years represent reference group.

[c]Non-Hispanic/Latino(a) participants represent reference group.

[d]Nonmarried participants represent reference group.

[e]White participants represent reference group.

[f]Nonrural participants represent reference group.

[g]Participants without dementia diagnosis represent reference group.

TABLE 4 Elastic net logistic regression models of health and well-being based on 18-month utilization.

	ADL deficits ≥3 (16.1%)		IADL deficits ≥3 (31.1%)		PROMIS depression Moderate/severe (14.2%)		PROMIS pain Moderate/severe (34.4%)		PROMIS sleep Mild–severe (24.1%)		PROMIS social support Very low/low (17.1%)		Self-reported health Fair/poor (30.1%)	
	Coef.	EME	Coef.	EME	Coef.	EME	Coef.	EME	Coef.	EME	Coef.	EME	Coef.	EME
Intercept	−3.81	-	−1.69	-	−6.07	-	−0.79	-	−2.38	-	−2.64	-	−0.22	-
18-month utilization														
ED	0.30	2.2%	0.00	0.0%	0.17	1.1%	0.14	1.7%	−0.14	−0.6%	0.11	0.8%	0.34	3.7%
IP	0.18	0.4%	0.14	0.4%	−0.29	−0.5%	−0.24	−0.8%	−0.05	−0.1%	−0.32	−0.7%	−0.06	−0.2%
PAC	0.11	0.1%	0.01	0.0%	0.24	0.1%	0.11	0.1%	0.28	0.1%	0.17	0.1%	0.39	0.4%
Female gender[a]	−0.79	−10.7%	0.00	0.0%	3.08	37.6%	−0.40	−9.0%	−0.72	−5.8%	0.73	10.3%	−1.16	−24.5%
Age group[b]														
70–79	1.49	20.2%	0.02	0.5%	0.68	8.3%	0.79	17.8%	0.70	5.6%	0.67	9.5%	0.63	13.2%
80–89	1.76	23.8%	0.25	5.4%	0.75	9.2%	0.29	6.5%	0.50	4.0%	0.48	6.8%	0.21	4.5%
90+	3.32	44.9%	1.82	39.1%	0.57	6.9%	0.24	5.4%	0.65	5.2%	0.47	6.7%	0.37	7.7%
Hispanic/Latino(a)[c]	0.85	11.5%	0.18	3.8%	0.17	2.1%	−0.64	−14.5%	0.82	6.6%	0.21	3.0%	0.76	15.9%
Married or living as married[d]	1.12	15.1%	0.65	13.8%	0.46	5.6%	0.35	7.9%	0.09	0.7%	−0.10	−1.4%	0.41	8.5%
Race[e]														
Black	0.58	7.8%	0.15	3.2%	0.00	0.1%	0.36	8.2%	−1.04	−8.4%	0.05	0.7%	0.03	0.6%
Other	0.77	10.5%	0.78	16.8%	0.99	12.1%	1.32	29.8%	1.03	8.3%	1.09	15.4%	0.07	1.5%
Rural status[f]	−0.19	−2.6%	−0.01	−0.3%	0.03	0.3%	−0.26	−5.9%	−0.25	−2.0%	−0.40	−5.7%	−0.28	−5.9%
Nosos prospective score	0.93	13.3%	0.48	10.8%	0.01	0.1%	0.46	10.9%	0.04	0.3%	0.43	6.5%	0.35	7.8%
Dementia diagnosis[g]	2.48	33.5%	3.48	74.5%	1.57	19.2%	−0.50	−11.3%	−0.12	−1.0%	1.32	18.7%	0.91	19.2%
Hyperparameters and model fit														
Missing n (%)	4 (1.0%)		4 (1.0%)		10 (2.5%)		14 (3.5%)		7 (1.8%)		14 (3.5%)		4 (1.0%)	
Alpha	0.59		0.43		0.10		0.35		0.10		0.10		0.84	
Lambda	0.00		0.01		0.00		0.00		0.01		0.00		0.00	
Cohen's kappa (test set)	0.11		0.12		−0.01		0.10		0.00		−0.06		0.07	

Note: Model coefficients (coef.) and estimated marginal effects (EMEs) derived from analysis on full training set (*n* = 399). For continuous variables (18-month utilization, Nosos prospective score), EMEs were calculated based on original unstandardized scales. Missing values resulted in case-wise deletion.

Abbreviations: ADL, activity of daily living; ED, emergency department; IADL, instrumental activity of daily living; IP, inpatient hospitalization; PAC, post-acute care facility; PROMIS, Patient-Reported Outcomes Measurement System 29-item Health Profile (PROMIS-29).

[a]Male participants represent reference group.
[b]Participants 65–69 years represent reference group.
[c]Non-Hispanic/Latino(a) participants represent reference group.
[d]Nonmarried participants represent reference group.
[e]White participants represent reference group.
[f]Nonrural participants represent reference group.
[g]Participants without dementia diagnosis represent reference group.

TABLE 5 Logistic regression models of health and well-being based on weighted and unweighted utilization variables.

	ADL deficits ≥3 (16.1%)	IADL deficits ≥3 (31.1%)	PROMIS depression Moderate/Severe (14.2%)	PROMIS pain Moderate/Severe (34.4%)	PROMIS sleep Mild–Severe (24.1%)	PROMIS social support Very Low/Low (17.1%)	Self-reported health Fair/poor (30.1%)
6-month utilization							
Weighted utilization day count							
ME (95% CI)	0.5% (0.1–0.9%)	0.7% (0.1–1.4%)	0.2% (−0.1–0.4%)	0.4% (−0.2–1.0%)	0.1% (−0.1–0.3%)	0.2% (−0.1–0.5%)	0.6% (−0.0–1.2%)
p-value	0.007	0.034	0.29	0.18	0.27	0.18	0.061
Unweighted utilization day count							
ME (95% CI)	0.6% (0.3–1.0%)	1.0% (0.3–1.7%)	0.1% (−0.2–0.4%)	0.2% (−0.3–0.7%)	0.1% (−0.1–0.3%)	0.2% (−0.1–0.5%)	0.7% (0.1–1.3%)
p-value	0.001	0.005	0.57	0.39	0.52	0.21	0.018
Difference test p-value	0.60	0.64	0.77	0.66	0.79	0.95	0.78
18-month utilization							
Weighted utilization day count							
ME (95% CI)	0.1% (0.0–0.3%)	0.1% (−0.1–0.2%)	0.1% (−0.0–0.2%)	0.2% (−0.0–0.4%)	0.1% (−0.0–0.1%)	0.1% (−0.0–0.2%)	0.4% (0.2–0.7%)
p-value	0.028	0.38	0.096	0.11	0.096	0.15	<0.001
Unweighted utilization day count							
ME (95% CI)	0.1% (0.0–0.3%)	0.2% (−0.0–0.4%)	0.1% (−0.0–0.2%)	0.1% (−0.1–0.2%)	0.1% (−0.0–0.1%)	0.1% (−0.0–0.2%)	0.2% (−0.0–0.5%)
p-value	0.021	0.063	0.13	0.46	0.11	0.22	0.075
Difference test p-value	0.87	0.33	0.83	0.41	0.90	0.79	0.23

Note: Model results, reported as estimated marginal effects (EME) and corresponding 95% confidence intervals, derived from analysis on full sample ($N = 570$). Both models included the same covariates used in the two elastic net models (gender, age group, ethnicity, marital status, race, rural status, Nosos score, and dementia status). Missing values resulted in case-wise deletion.

Abbreviations: ADL, activity of daily living; IADL, instrumental activity of daily living; PROMIS, Patient-Reported Outcomes Measurement System 29-item Health Profile (PROMIS-29).

predicted and observed outcomes, this time for ADL deficits, IADL deficits, and pain. In contrast to the 6-month utilization results, no single setting of health care utilization during the prior 18-month interval emerged as most related to QoL. PAC utilization was the most salient predictor of sleep dysfunction and poor self-reported health, with 1 day of PAC associated with a 0.1% increase in the probability of sleep dysfunction and a 0.4% increase in the probability of sleep dysfunction. ED utilization was the strongest predictor of ADL deficits (2.2%), and IP utilization was the strongest predictor of IADL deficits (0.4%). Again, as in the 6-month models, more IP utilization was associated with decreased rates of poor QoL outcomes in five out of seven models. However, ED utilization was associated with decreased rates (−0.6%) of poor QoL outcomes in the sleep dysfunction model only.

Results of the weighted and unweighted utilization models are reported in Table 5. According to those, weighted and unweighted 6-month utilization variables were associated with increased rates of ≥3 ADL and IADL deficits, such that each weighted day of utilization was associated with a 0.5% (95% CI: 0.1%–0.9%) greater rate of ADL deficits and a 0.7% (95% CI: 0.1%–1.4%) greater rate of IADL deficits, and each unweighted day of utilization was associated with a 0.6% (95% CI: 0.3%–1.0%) greater rate of ADL deficits and a 1.0% (95% CI: 0.3%–1.7%) greater rate of IADL deficits. The unweighted count of days of health care utilization was also associated with a greater rate (0.7%, 95% CI: 0.1%–1.3%) of fair/poor self-reported health, whereas the weighted count was not (0.6%, 95% CI: −0.0% to 1.2%). There were no significant differences between the coefficients for weighted and unweighted utilization (*p*s >0.60). Similarly, in the 18-month models, both weighted (0.1%, 95% CI: 0.0%–0.3%) and unweighted utilization (0.1%, 95% CI: 0.0%–0.3%) were associated with greater rates of ≥3 ADL deficits. The weighted utilization variable was associated with a greater rate (0.4%, 95% CI: 0.2%–0.7%) of fair/poor health, whereas the unweighted utilization variable was not (0.2%, 95% CI: −0.0% to 0.5%). Again, there were no significant differences between the coefficients for weighted and unweighted utilization (*p*s >0.23).

4 | DISCUSSION

A growing body of scientific literature has evaluated measures of home time in relation to patient-centered QoL.[1,7,14,15,30–32] However, no prior research had examined differences in the association of health care utilization with patient QoL by context, nor investigated whether short-term versus long-term utilization was most associated with QoL. In the present study, we did just that, examining which types of health care utilization are most associated with measures of QoL and over what duration. According to our results, setting is clearly important, such that the impact of receiving care in one setting is not equivalent to that in another setting. Despite only 3% of the sample having any PAC care, greater utilization of PAC was the most closely related to reduction in the QoL indicators in six of the seven 6-month QoL models. This compares to the unexpected finding that greater IP and ED utilization were associated with increases in the

majority of QoL outcomes. Results at 18 months were less clear across all settings of care. Regarding our secondary goal, we found that weighted and unweighted 6- and 18-month measures of time away from home were associated with greater rates of ADL deficits. Utilization sums were also significantly associated with greater rates of IADL deficits and fair/poor health, albeit not consistently so across weighted and unweighted 6- and 18-month utilization measures. Neither the unweighted nor the weighted measure of home time outperformed the other in direct comparisons.

Our goal with this paper was to improve patient-centered measurement of home time by making evidence-based recommendations as to which care settings to include, how those settings might be weighted, and the importance of the time period in measuring home time. While we have done that, important limitations prevent us from making stronger recommendations, particularly with regard to weights and the implications for QoL. For one, even though we used measures that we (and many others) agree are relevant for QoL and are person-centered, we did not have health utility measures. Other work has established good convergent validity between the PROMIS-29 domains—including the PROMIS global self-rated health measure— and EQ-5D utility measures,[18] meaning that they capture similar aspects of health. However, whereas self-rated health from the PROMIS battery is considered to be a global health measure, a possible limitation is that it has been shown to be influenced by health expectations[33] and has low responsiveness to change. The self-rated health findings here are consistent with Lee and team's research[14] using unadjusted models of days alive and not at home and person-centered outcomes. They found that Medicare beneficiaries were three percentage points more likely to be in poor self-rated health if they remained at home only 358 days compared with 365 days. Regarding function's relatedness to global QoL, other research has shown higher ADL and IADL functions were each associated with QoL[34]; however, a hypothetical scenario study showed that ADLs were not related to health utilities.[35] Overall, our models captured varying aspects of QoL and thus demonstrated considerable variability with regard to the magnitude of the associations of health care utilization with the measured QoL outcomes. Future analyses aimed at refining definitions of home time would benefit from having access to utility-based QoL measures for older adults that reflect health status, such as EQ-5D-5L or EuroQol, or newer measures that "capture emotional sentiment towards personal circumstances," such as the ASCOT or ICECAP.[36]

A key goal of this project was to try to uncover and then recommend weights for the individual settings included in home time, based on what mattered to patients. For instance, if all settings of utilization had negative associations with QoL, a formula might look something like "total weighted days away from home = 1.25 * ED + 1.5 * IP + 2 * SNF." Proposing such a weighting scheme could move us closer to arriving at a weighted population-health measure of home time that reflects patient QoL. However, based on our results from the current study, in which we used existing data from a cohort of older adult male veterans, recommending weights does not appear to be a viable approach for capturing the impact of health care utilization on this array of measures.

Essentially, we found that there were very different associations between individual settings of care and QoL. Second, there was substantial variation in how settings of care related to the seven individual QoL measures (some negative, some positive, some strong, and some weak). The weighted measure was a count of days at 6 (and 18) months based on individual weights for each distinct setting of care, whereas the unweighted measure was a cumulative count of days in any of the assessed settings at 6 (and 18) months. The high variation we observed makes it unsurprising that the weighted measure of home time did not outperform the unweighted measure. Regardless of the time period over which days are observed (6 or 18 months), no single set of weights captured the variation in the association that we saw across settings of care (ED, IP, and PAC) and across individual QoL outcomes.

Still, our findings are important. We found that the associations of settings with outcome varied substantially by QoL. In other words, we found that the type of setting in which a patient receives treatment is differentially associated with QoL. Moreover, we found that ED settings matter and are important to include in a home time measure. Time in the ED setting is not commonly included in home time measures in part because an ED visit may not necessarily take up a person's whole day and also because much of the literature starts counting home time after the date of an IP admission.[8]

Furthermore, we found that the time period over which we measure utilization matters. The 6-month results gave us a clear indication that PAC utilization is most strongly associated with QoL measures (in six out of seven QoL measures). However, in the 18-month models, we did not see such consistency. This may reflect recency effects, such as having utilization occur closer to the time QoL was assessed by survey; it could also reflect that the relationship between home time and QoL is weaker and more variable at 18 months. We had expected that recent health care utilization might yield different associations with QoL and it did. In the short term, ED utilization was more salient than it was in the long term (even with unexpected signs). This suggests that the time frame over which to measure home time should fit the particular research question.

We also had some counterintuitive findings, such as positive associations between more time away from home and higher QoL. This occurred more in the ED and IP settings of care at 6 months, implying that more utilization is associated with better QoL outcomes. We generally expected a negative relationship between the two, but again, if a person is getting needed care during this episode, it makes sense that the relationship could be positive, as that episode addressed the primary problem. Many of the negative outcomes from IP care, for example, arise from secondary problems (e.g., functional decline from lack of mobility, delirium, and hospital-acquired infections).[37–39] It is also important to note that these models estimate the average effect per day. However, the impact of utilization is not necessarily linear across time, and the reasons for care may have differential effects. While we explored an average effect in this work, differential effects by reason for care may be an area for future research.

Other features of this study need to be considered. We worked hard to have completeness of the health care utilization data given that our study consisted of veterans and that most VA users access multiple systems of care. We carefully tracked utilization in the settings under consideration using VA, VA-financed, and CMS data, including means of obtaining Medicare Advantage utilization using MedPAR and MDS files (as opposed to fee-for-service, for which we have individual claims). The use of MDS allowed us to capture PAC stays for veterans covered by any CMS payer as well as privately paid PAC care occurring in Medicare- or Medicaid-certified facilities. Although we did not obtain Medicaid claims, Medicare is the primary payer for dual Medicare–Medicaid beneficiaries, so we did capture dual beneficiary utilization. And although we captured most utilization of interest across multiple systems, we could not capture all Medicare-financed ED days for Medicare Advantage veterans, because those are not included in CMS claims data (some ED use could have appeared in MedPAR files, which we captured). We felt that the gains of including veterans with Medicare Advantage still merited including these veterans, and yet, the association between ED and the person-reported outcomes found could be due in part to underreported ED use if veterans were on Medicare Advantage and VA did not pay for any of the ED visit. That said, most prior research studies on home time have considered only one payer[7–16,37,40] So there has likely been measurement error for patients with multiple insurance sources. Overall, our approach minimized measurement error on the home time measure.

While the data issues discussed limit the conclusiveness of the present findings, there are several improvements we and others can make to revisit whether weighting is merited for a population-level home time measure for older adults. First, we can test weighting using a different data set using a global QoL measure, especially validated health utility measures. Second, we can find data that allow us to control for pre-utilization QoL to be more confident that any association we estimate is due to the time in the setting and not the underlying difference in QoL that existed in advance of the utilization occurring. Third, future work should tease out any differences in experiences for patients in planned versus unplanned hospitalizations. It is possible that some of the positive effects we found were due to expected care that was needed. Fourth and finally, to make progress in the validation of a home time measure that is optimally person-centered for the population, we need to test it in more diverse samples than we had available.

In sum, despite the above limitations, this project can serve as a template for future work aimed at developing a more granular measure of home time. Specifically, results from this study and the methodologies employed herein can be used to inform decisions about which health care settings to include, which time frames to consider, and possible ways to develop weighting schemes using different data. Importantly, we found a close relationship between unweighted summed days in these settings and worse QoL, which is a novel finding, suggesting that our home time measure is person-centered. In turn, the value of such a home time metric constructed from claims

data is that it ultimately could be used to evaluate patient-centered outcomes in the absence of directly reported measures of QoL.[14]

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