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The Utility of Public Health Survey Validation: Assess Psychometrics as a Means of Improving Patient Outcomes

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THE UTILITY OF PUBLIC HEALTH SURVEY VALIDATION: ASSESS PSYCHOMETRICS AS A MEANS OF IMPROVING PATIENT OUTCOMES

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Richard A. Muñoz

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To: Dean Tomás R. Guilarte
Robert Stempel College of Public Health and Social Work

This dissertation, written by Richard A. Muñoz and entitled The Utility of Public Health Survey Validation: Assess Psychometrics as a Means of Improving Patient Outcomes, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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DEDICATION

I dedicate this dissertation to…

My grandparents that raised me,

My parents that were there for me,

My friends that encouraged me,

To those that loved me,

To those that will love me,

My mentors that trained me,

My colleagues that collaborated with me,

To everyone that believed in me,

To the lessons that I needed to learn,

To the ones I am eager to learn,

To the challenges I have overcome,

To the challenges I yearn to overcome,

To myself…

To being too stubborn to quit.

😊

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Family, friends, community members, colleagues from other professional paths

ABSTRACT OF THE DISSERTATION

THE UTILITY OF PUBLIC HEALTH SURVEY VALIDATION:

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Florida International University, 2023

Miami, Florida

Professor Zoran Bursac, Major Professor

In this dissertation, we discuss how population-based public health psychometric survey validation, through the lens of health systems research, can help healthcare administrators, stakeholders, and advocates, better understand various types of health factors, and how they relate to tangible real-world outcomes. The research conducted here informs health policy, with recommendations for targeted interventions that aide in ameliorating or lessening the burden of adverse outcomes, and ways to further extrapolate this work towards other health systems and populations.

The first chapter champions a global health collaboration between Florida International University and over 30 hospitals within 5 Latin American countries. We collected survey data measuring patient safety culture and assessed the psychometric properties of the Agency for Healthcare Research & Quality's Version 1 Spanish-translated Hospital Survey on Patient Safety Culture. We also tailored five country-specific models to gauge the intersection between gains in validity versus comparable utility between Latin America regionally or within countries.

The second chapter is a pilot study called the "High-Need, High-Risk"-658, which was conducted at the Miami, Florida Veteran Affairs Medical Center, where we assessed which factors were related to acute-care utilization measures (emergency room stays, and inpatient hospital stays). We also grouped Veterans into clinically relevant and meaningful latent classes, approximated latent class inclusion, and discovered which survey items endorsed class membership. For the last chapter, we used the lessons learned and survey items used in the pilot study to assess the cross-sectional first time-wave of data collected from the parent Home Excellence Resource Center to Advance, Redefine, and Evaluate Non-Institutional Care (HERO CARE) survey. We assessed its psychometric properties and which health factors were related to acute-care usage and unmet needs.

Word Count: 275

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ABBREVIATIONS AND ACRONYMS

AHRQ – Agency for Healthcare Research & Quality

AIC – Akaike Information Criteria

BIC – Bayesian Information Criteria

CFA – Confirmatory Factor Analysis

CFI – Comparative Fit Index

EFA – Exploratory Factor Analysis

FIU – Florida International University

GECDAC – Geriatrics Extended Care Data Analysis Center

GRECC – Geriatrics, Research, & Education, Clinical Center

HERO Care – Home Excellence Resource Center to Advance, Redefine, and Evaluate Non-Institutional Care

HMA – Healthcare Management Americas

HNHR – High-Need, High-Risk

HSOPSC – Hospital Survey on Patient Safety Culture
Institutional Care

LatAm – Latin America

LCA – Latent Class Analysis

RMSEA – Root Mean Square Error Approximation

SRMR – Standardized Root Mean Residual

TLI – Tucker-Lewis Index

v1, v2 – Version 1, Version 2

VA – Department of Veterans Affairs

VAMC – Veterans Affairs Medical Center

VISN – Veteran Integrated Service Network

INTRODUCTION

From a global health perspective, one out of four hospitalizations of low- to middle-income countries has an adverse event. Little is known about how factors affect unsafe care globally. Surveys are often used in public health and politicians often use their data to make policy-informing decisions. However, these tools are not always validated. Focusing on the United States, the top five percent of the costliest patients account for over fifty percent of healthcare costs, representing a 10-fold differential! Per a 2021 Commonwealth report, one third of adults will need long-term care by retirement age, which equivocates to about $100,000 per year per person, at personal expense. Also, hospital care will be the leading dimension of healthcare costs in the United States, accounting for 31% of the cost-pie, approximating to about $1.3 trillion.

This dissertation addresses both issues by using population-based public health psychometric survey validation, from a health systems research perspective, to validate surveys measuring patient safety culture (Chapter 1), and health factors associated with acute-care utilization (emergency room stays, and inpatient hospital stays) and patient's unmet needs (Chapter 2 and 3). The results of this work will help healthcare administrators, stakeholders, and advocates to better understand various types of patient safety culture factors to improve patient care and safety. This dissertation's results will also explore health factors, and how they relate to tangible real-world outcomes.

The research conducted here informs health policy, with recommendations for targeted interventions that aide in lessening the burden of adverse outcomes, and ways to further extrapolate this work towards other health systems and populations.

CHAPTER 1

VALIDATION OF THE HOSPITAL SURVEY ON PATIENT SAFETY CULTURE IN FIVE LATIN AMERICAN COUNTRIES

ABSTRACT

Florida International University's Healthcare Management Americas and other stakeholders assessed if a regional United States Spanish-translated Hospital Survey on Patient Safety Culture (version 1) from the Agency of Healthcare Research & Quality was applicable in 5 Latin American countries (Argentina, Chile, Colombia, Honduras, and Peru) that primarily speak Spanish. Using data from 32 hospitals including 5,855 hospital staff respondents, we built 5 country-specific models using exploratory factor analyses to test the dimensionality of the regional model within each country's contexts, and Pearson correlation matrices to refine those models. Confirmatory factor analysis was used to assess construct validity by comparing the country-specific versus regional model data across a 1000-replication bootstrap of 95% confidence intervals of model fit indices. Internal consistency was calculating using Cronbach's alpha of each regional versus country-specific factor. While the country-specific model fits the Chile country-data better, we ultimately support a regional model due to its potential for regional learning to improve patient safety across Latin America.

Word Count: 159

Key terms: Patient Safety Culture, Latin America, Validity, Reliability, Bootstrap, Survey

INTRODUCTION

Population-based public health psychometric survey validation, using a health systems approach, can help provide low-cost, validated derivative of a shared latent trait that while are not exclusively clinical, can affect health and healthcare infrastructure performance, quality of care, and the health of patients, their families, communities, and health system at large. Evidence-based research can inform health policy that helps (re)direct resources to health and healthcare infrastructure areas that need help towards a common, prioritized goal, such as reducing adverse hospital events, reducing hospital staff error, and improving patient safety culture – a shared goal among patient's communities, hospitals, risk management advocates, and administrative and policy stakeholders.

It is estimated that one of every four hospitalizations in low- and middle-income countries (LMICs) has an adverse event[1]. Despite the significant burden of unsafe care in LMICs, there is a lack of knowledge regarding the factors that contribute to unsafe care on a global scale. One such factor, as identified by the World Health Organization (WHO) World Alliance for Patient Safety, is patient safety culture[2]. This refers to the values, perceptions, and behaviors that determine an organization's commitment to health and safety management[3]. The measurement of patient safety culture can assist healthcare facilities in identifying gaps and interventions required to improve safety culture, which is why it has been included in the strategic objectives of the WHO Global Patient Safety Action Plan 2021-2030[4]. However, assessing patient safety culture globally necessitates a balance between the psychometric properties of the instrument and its utility for global benchmarking and learning. While a country-specific measurement model could achieve the highest validity, it could become impractical as a learning system if the measurement is not comparable to similar countries. Facing a similar dilemma for quality indicators in low-resource settings, the National Academies' Committee on Improving the Quality of Health Care Globally suggested utilizing existing measurements instead of creating new ones that demand more resources[1].

The HSOPSC is a survey instrument developed by the agency for Healthcare Research and Quality (AHRQ) that was created for and psychometrically validated within the context of U.S. hospitals in 2007; this work led to the development of a 12-factor measurement model[5-7]. By 2009, it was validated in Spanish[8], but tailored to the cultural, linguistic, and healthcare infrastructure context of United States hospitals. The results from a literature review done in 2019 indicated not only that the HSOPSC psychometric properties were already translated into Spanish in Latin America – though for only for one country – but also across 62 different countries[7]. There is a need to attempt to validate this survey not just within a country's context, but across an entire region that incorporates various countries, with the aim to help interconnected geographical regions of collaborating countries help improve patient safety culture, together. Another research gap on this topic is whether investing resources for validating and translating the survey to each regions separate countries yield more utility in measuring patient safety culture than saving those resources and just use the regional model across a region that speaks the same primary language.

The aim of this study was to compare two underlying factor structures: a regional model based on the 12-factor U.S. original model (HSOPSC-R), and a country-specific (HSOPSC-CS) model based on the best factor-structure for each specific country, to address both the need to maximize the focal point between the best performing (psychometrically) versus most broadly applicable (utile) HSOPSC version 1 survey, and the need to make an evidence-based recommendation to either invest in tailoring the survey to each Latin American country's context, or save those resources and use the regional survey to help hospitals across Latin America to improve patient safety culture, uniformly.

To do this, we studied the psychometric properties of the first, Spanish-language version of the Hospital Survey on Patient Safety Culture (HSOPSC v1). We first used exploratory factor analyses and Pearson correlation matrices to define and refine the HSOPSC-CS models, respectively. Then, we assessed the gains in terms of internal reliability and construct validity of the HSOPSC-CS model compared to the HSOPSC-R model. The data collection was performed by Healthcare Management Americas (HMA) in collaboration with 33 hospitals from Argentina, Chile, Colombia, Peru, and Honduras, representing a total of 5,855 hospital staff. Data was collected from November 2018 to February 2020, before the COVID-19 pandemic.

Again, while the HSOPSC psychometric properties have been explored in different countries[7], this is the first study to include multiple countries from the same region. This pushes the envelope of whether policy and investment stakeholders should invest in country-specific Spanish-translated patient safety culture survey, or just use the base United States regional one.

METHODS

Instrument

According to the AHRQ, their 2009 United States Spanish-translation process involved several steps and various stakeholders[8]. The original Spanish translation of the facility version of the HSOPSC was performed by Premier Inc., and later pretested by Westat using cognitive interviews, to which then revisions were made. After back-and-forth revisions based off recommendations from a bilingual survey translator, the finalized Spanish version of the HSOPSC v1 consisted of Westat's translation review and revisions of the initial Premier translation.

The United States Spanish-translated Hospital Survey on Patient Safety Culture – Regional model (HSOPSC – R), spans 12 patient safety culture domains, across a total of 42 survey items. All 42 items are anchored on five Likert response levels. While all the items have the same number of response options, the language used to bind them varies slightly. For 9 domains, the items within them ranged from 1 – "Strongly Disagree," 2 – "Disagree," 3 – "Neither Agree nor Disagree," 4 – "Agree," and 5 – "Strongly Agree." For the three remaining domains, these items still had the same ordinal range of integers, but these were their response labels: 1 – "Never," 2 – "Rarely," 3 – "Sometimes," 4 – "Most of the time," 5 – "Always." These three domains were as follows: Feedback & Communication About Error, Communication Openness, and Frequency of Events Reported; the decision to label the items differently is a common survey design occurrence and revolves around wrapping the qualitative context of the item's wording around the latent trait they are intended to measure[5]. Though in this instance these decisions are more qualitatively driven, there are indeed statistical reasons for item wording choices when designing surveys, such as not using negatively-worded items. Negatively-worded items are problematic psychometrically because they load on different factors than the ones they are intended to measure, which affects the accuracy of the health concepts we are intending to measure.

Data Sources

The survey data was collected from 32 hospitals across 5 Latin American countries (Argentina, Chile, Colombia, Honduras, Peru) that volunteered to administer the United States Spanish-translated Hospital Survey of Patient Safety Culture version 1 survey, spanning 5,855 total hospital staff respondents. A range of interactions led to these collaborations, whether there were relationships initiated by Healthcare Management Americas (HMA) at Florida International University (FIU) or other stakeholders to administrators from these hospitals, or other administrators reached out electronically to HMA at FIU and solicited this service to be provided to their hospital. This service that HMA at FIU provides has three phases.

It begins with training the hospital administrator on how to administer the survey, plus methods for outreach to incentivize staff to take the survey. Next, the survey respondents are convenience-based sampled that work at the hospitals and their responses are anonymous, with no respondent-specific identifiers, and with the promise from HMA at FIU to respondents that they will not be uniquely identifiable. Finally, once the data is collected, the final report is created and tailored to each country, with visual heuristics representing the scaled scores of each of the 12 domains.

The final debriefing to the hospital administrators by the HMA primary investigator includes comparisons of the hospital's scores to the averages of other hospitals surveyed in their country, and averages of United States hospital scores from data within the Agency of Healthcare and Research Quality's (AHRQ) database. The debriefing also includes targeted interventions and training for selected hospital staff (chosen by the administrators) to undergo patient safety and risk management training. The service is free-of-charge for the hospitals involved, along with the semi-annual training administered at FIU. Ergo, HMA at FIU and other stakeholders have no financial commitments to report.

Data Management

The master data file consists of the responses gathered from the patient safety culture survey administrations to hospitals within the 5 sampled Latin American (LatAm) countries, between 2018 and February 2020, just before the COVID-19 pandemic hit LatAm. It was partitioned into five distinct analytic datasets containing each country's respective survey responses. After the data management phase, data screening was performed using SPSS version 28[9], and consisted of descriptive statistics of the item means and standard deviations, handling of missing data (missing cases were dropped regardless of missingness percentage), and skewness and kurtosis of the items were estimated to check their normality – see Table 1-1 for the HSOPSC-R model structure and item-leveled descriptive statistics. The same software was used to calculate the various hospital-level demographic characteristics of the respondents taking the survey, by country – see Table 1-2. Mplus version 8.5[10], and Stata version 17[11] were used below for the factor analyses and bootstrap methods respectively.

Country-Specific Models (HSOPSC-CS)

In order to test if the regional model was better than respective country-specific models, the latter were built statistically first; we built five HSOPSC-CS models (one for each LatAm country represented in the data). Using exploratory factor analysis (EFA), the researchers explored the dimensionality of the country-data, gauging which items loaded onto which factors based on factor loadings (the correlations between the survey items and an underlying factor) – analogous to an "outer frame" or "layout" of the model. In Mplus, Geomin Rotation, Oblique type, was used because it was assumed that the 12 domains within the HSOPSC-R were highly correlated[12]. Geomin rotation was also chosen because it is particularly robust when the factor loading structure is complex, the sample size and communalities are large enough, and it can provide similar rotation solutions to confirmatory factor analyses produced solutions by various models in simulation studies[13].

The estimation method used was robust maximum likelihood (RMLE) estimation for continuous variables because this method can handle data that is not normally distributed, or when independence of observations cannot be assumed[14]. There is evidence to suggest that when items have at least five response levels or more, they can be considered continuous[15,16], which is why the survey data (consisting of 42 items anchored by 5 response levels each) was treated with a continuous estimation method. With statistical applications involving estimations of data that are typically dependent on uncertainties, especially considering respondents' individual and unique characteristics and anatomies, RMLE is used to protect against data errors and has been found to lead to more reliable results and decisions when applied to large datasets[17].

Once preliminary exploratory factor analytic methods were performed to justify the number of factors for each respective HSOPSC-CS model (using Pearson product moment correlation matrices), the factor-structures within each model were refined. To decide which number of factors best fit the data for each country, there were several methods that helped reach those conclusions. Scree plots were created and incorporated with the Kaiser Criterion (KC: smallest eigenvalue that is closest to yet also greater than 1)[18]. Parallel analysis (PA) was also considered and performed, but ultimately not incorporated because the number of factors that the method suggested in comparison to those by the Kaiser criterion method were significantly lower by an average of at least 2 less factors for each country. While Sheytanova's research supports that the Kaiser Criterion tends to overestimate the number of factors and parallel analysis tends to be more robust and accurate, the researcher also mentions that parallel analysis is not universal and recommends that various methods be implemented when determining the dimensionality of a latent construct[19].

There were several considerations that informed which model building metric would justify which model would be built. The Kaiser criterion model building metric suggests that the best-fitting model is the one that essentially is the closet one that just hovers over an eigenvalue of 1.000. Parallel analysis was another method considered, and it is done by calculating the eigenvalues for each factor-model of the real dataset and compares them to one from simulated data. The best-fitting model based on parallel analysis is the factor-model where the real dataset eigenvalue is larger than the simulated one. Finally, we also used screeplots, where a screeplot is basically a scatterplot of the two methods above, with a y-axis of eigenvalues and an x-axis of the number of factors the model would have and connected as line segments. For both the Kaiser criterion and parallel analysis methods, a screeplot was created for each country by plotting the corresponding x-y coordinates from each method on the same graph, to help visualize and inform the model building process.

Regarding the model-building decision-making process, both the Kaiser criterion and parallel analysis methods reported smaller factor models than the base 12-factor model; this was consistent with other researchers' validation studies[7]. However, the Kaiser criterion method suggested factor models that although smaller, were more closely related to the base regional model than the parallel analysis method. The KC method results also made more sense practically and theoretically because there was a more balanced mixture of items per factor, and also the collection of items per factor made more sense qualitatively when determining the latent traits they measured. Factor loadings were calculated for each

LatAm country-data with the following considerations, that they were statistically significant at the alpha level of 0.05, and with a magnitude of at least 0.300[20].

HSOPSC-CS Refinement using Correlation Matrices

All correlations between and using the scaled items were calculated using Pearson's Product-Moment Correlation (*r*) because the response levels were assumed to be continuous, and the normality assumption was upheld. As such, Item-Factor, Inter-Item, Inter-Factor, and Within-Factor correlations were run, each for relevant model building reasons towards constructing each Hospital Survey on Patient Safety Culture (HSOPSC-CS model), by country. Item-Factor correlations were used as a major indicator of which factors items congregated to, because factor loadings and inter-factor correlations are dissimilar when factors are highly correlated (which is why oblique rotation was used).

Inter-item correlations were performed to gauge if the intercorrelations were optimally within the range of +/- 0.3 to +/- 0.8, and correlations outside of this range were considered problematic. Inter-factor correlations were calculated to gauge if the composites themselves were highly correlated, which would suggest multicollinearity measuring the same construct, just from different perspectives either negatively or positively worded. Also, statistically significant inter-factor correlations could suggest that second-order levelling of the factors could be more appropriate[21].

Within-factor correlations (Pearson correlations of the items within the factors they loaded onto together) were calculated by analyzing the average inter-item correlations within each subscale and gauging if they were within the optimal range between 0.15 to 0.5, where below the lower threshold would imply that it would be unlikely that the total score would relate to the underlying construct, and a correlation above the upper limit would show that the scale would be overly redundant and/or the construct would be too specific[22].

Once the finalized models were drafted, confirmatory factor analyses were performed to test if the hypothesized model "frames" fit the data well. Further refinement of the HSOPSC-CS models was done through applying modification indices (results-driven improvements in overall chi-square model fit suggested by the software to load certain items on other factors to improve model fit statistically). This process was replicated five times, once for each set of LatAm country-data.

Comparing the HSOPSC-R and HSOPSC-CS Models

Confirmatory Factor Analyses (CFA)

To assess if the hypothesized HSOPSC-CS models fit the five LatAm country data better than the base of comparison HSOPSC-R model, Confirmatory Factor Analyses (CFA) were performed. To assess model fit, global fit indices were calculated. For global fit, the overall model chi-square statistic was calculated, where a nonsignificant test statistic would show that the model fit is adequate. Because it is mainly a good measure when the sample sizes are less than 200, which is not the case here, other model fit estimates were provided. Incremental fit indices were calculated: The Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI), and absolute fit indices were also calculated: Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Residual (SRMR). The cutoffs for these fit indices above were set at the industry standards of at least 0.9 for CFI and TLI for good fit, with at least 0.95 for great fit, and at most 0.07 and 0.08 for RMSEA and SRMR, respectively, for good fit[23,24].

A relevant point tying in the HSOPSC-CS model building process with performing the CFA is that once all the procedures for building the HSOPSC-CS models (mentioned above) were performed for each country, the final model-building decision came after running an initial CFA, to estimate and incorporate the single highest modification index that suggested the largest improvement in model fit. Modification indices (MI) are statistical suggestions based off the CFA computations for the largest improvement in overall model fit chi-square estimates, meaning the largest reduction or smallest possible value for chi-squared if the model were rerun using the suggested change – loading an item on a different composite. MI are also called LaGrange Multipliers or Score Tests, and the process of adding a large MI is called a "post-hoc model modification," and while this approach is mainly data-driven and less on a hypothetical framework or theory, often resulting information from applying MI can lead to a deeper understanding about a possibly more complex model structure than what the *a priori* hypothesized model suggests[25,26].

Bootstrap 95% Confidence Intervals of CFA Fit Estimates (Bootstrap CFA)

Using Stata version 17, bootstrap 95% confidence intervals of the model fit estimates CFI, TLI, RMSEA, and SRMR mentioned above were performed to provide more accurate estimates that could be compared between the HSOPSC-R and HSOPSC-CS models. Bootstrapping is a data-based, computer-driven, computationally heavy, and lengthy statistical and resampling method that was developed in 1982, but became more popular with the advent of computers, and has continued to be refined as computers and statistical software have been further developed. The Bootstrap is the resampling, with replacement, of an experimental dataset into smaller, close approximations of its original, whereby the statistical estimate(s) of choice are calculated in each of these smaller bootstrap replicates. It is a deterministic resampling application that uses pseudo-random number generation (PRNG) to create the bootstrap replicates, whereby the sample statistic(s) of interest are then calculated and pooled together into a normal distribution because they have approached normality through the properties of the Central Limit Theorem.

To compare the HSOPSC-R and HSOPSC-CS models for each country, percentile-corrected 95% confidence intervals were constructed, where if the intervals did not overlap each other, and one of the intervals was closer to the preferred threshold value that was appropriate for the given fit indices, then that model would be considered the better fitting model, per 1000 replicated comparisons[27]. Percentile-corrected interval construction occurs as follows: once a 1000 bootstrap replicates have been created, rank-order the estimated sampling statistic(s) of choice that were calculated, and the 25^{th} and 975^{th} values would be the lower and upper bounds of the bootstrap 95% confidence interval, binding that estimate, respectively. Nevertheless, it is not uncommon for the bootstrap distribution to be skewed, hence corrections have been developed such as the percentile-corrected and the bias-corrected and accelerated bootstrap. A simulation study performed by Kwanghee et al. found that percentile-corrected confidence intervals produced boundaries that were closer to the desired level of coverage when compared to bias-corrected and accelerated bootstrap (BCa) and Student's *t* confidence interval estimation methods. While they also found that the BCa method was less prone to imbalance, but still too narrow than the desired coverage, percentile-method outperformed overall, and thus was the type of estimation provided in tables below[28].

Validity and Reliability Testing

To assess which of the two models, the HSOPSC-R or the HSOPSC-CS models, were more valid and reliable in measuring the latent construct of patient safety culture in hospitals within five LatAm countries (Argentina, Chile, Colombia, Honduras, and Peru), validity and reliability testing were performed. The types of validity specifically measured in this study are construct validity – how well certain items in a scale adequately correlate and conjointly explain a large variation in the response patterns of respondents – and discriminant validity – how well certain items in the same scales do not correlate with other items (to avoid multicollinearity). To measure construct validity and discriminant validity, inter-item correlations were tested for their statistical significance, at the conventional 5% significance level, whereby correlations below the former lower criteria (r = +/- 0.3) suggest weak construct validity and correlations above the latter upper limit (r = +/- 0.8) suggest weak discriminant validity[29].

The most widely used objective measure of reliability is Cronbach alpha[30], to provide a measure of the internal consistency of a test or scale. Instead of calculating one overall Cronbach's alpha for the entire test, it is recommended to calculate one for each factor, to test the unidimensionality of the sub-scales/factors, especially when the number of test items are adequate Otherwise, if the number of test items is too small that tends to underestimate reliability. For this reason, it was important to precisely estimate the number of survey items for each sub-scale within each HSOPSC-CS model (per country), which helped gauge how homogeneous each factor was, and how consistent the items behaved in unison measuring each factor's latent trait.[31] Essentially, while validity is akin to the accuracy of the instrument, reliability assesses its precision. To measure the reliability of the base HSOPSC-R and the hypothesized HSOPSC-CS model composites for each country, internal consistency was measured by calculating a Cronbach's Alpha statistic for each subscale, with a cutoff of greater than 0.7 indicating an acceptable level of reliability[32]. Internal consistency can be described as the propensity of different respondents to answer a survey in similar ways, with similar response patterns.

RESULTS

Item-Level & Respondent-Level Demographics

Table 1-1 is the HSOPSC-R model structure and item means, grouped by each of the five LatAm country's hospital data represented in the study with the full description of the item means, standard deviations, and measures of skewness and kurtosis. (See the full Table1-1 in the Appendix). Because all the survey items/questions are anchored on a Likert scale from 1 to 5, the higher the value of the item mean, the more the survey respondents resonate with what is being asked happens "most of the time" or "always," or they either "agree" or "strongly agree" with the statement they rated. Items with asterisks (*) in Table 1-1 were negatively worded. And thus, those items were reverse coded. Below you will find a summary of Table 1-1 that includes the HSOPSC-R model structure survey item means, grouped by the 5 LatAm countries.

***Table 1-1*: USA HSOPSC-R model structure & item means, by country**

Item	U.S. Subscales/Description	Argentina	Chile	Colombia	Honduras	Peru
	Teamwork within Units					
A1	People support one another in this unit.	3.81	4.05	4.06	4.20	3.74
A3	When a lot of work needs to be done quickly, we work together as a team to get the work done.	3.94	4.00	3.95	4.18	3.70
A4	In this unit, people treat each other with respect.	4.02	4.28	4.22	4.25	3.87
A11	When one area in this unit gets really busy, others help out.	2.81	3.00	3.23	3.58	3.10

Supervisor/Manager Expectations & Actions Promoting Patient Safety						
B1	My supervisor/manager says a good word when he/she sees a job done according to established patient safety procedures.	3.47	3.84	3.73	3.88	3.59
B2	My supervisor/manager seriously considers staff suggestions for improving patient safety.	3.51	3.90	3.81	3.89	3.58
B3*	Whenever pressure builds up, my supervisor/manager wants us to work faster, even if it means taking shortcuts.	3.20	3.26	3.13	3.06	3.05
B4*	My supervisor/manager overlooks patient safety problems that happen over and over.	3.83	4.06	3.81	3.88	3.70
Organizational Learning - Continuous Improvement						
A6	We are actively doing things to improve patient safety.	4.05	4.11	4.19	4.37	3.95
A9	Mistakes have led to positive changes here.	3.79	3.81	3.89	4.04	3.67
A13	After we make changes to improve patient safety, we evaluate their effectiveness.	3.60	3.65	3.90	4.00	3.68
Management Support for Patient Safety						
F1	Hospital management provides a work climate that promotes patient safety.	3.96	3.96	3.93	4.42	3.64
F8	The actions of hospital management show that patient safety is a top priority.	4.11	4.03	4.12	4.39	3.82
F9*	Hospital management seems interested in patient safety only after an adverse event happens.	3.34	3.42	3.51	3.49	3.23
Overall Perceptions of Patient Safety						
A10*	It is just by chance that more serious mistakes don’t happen around here.	3.56	3.59	3.25	2.86	3.14
A15	Patient safety is never sacrificed to get more work done.	3.33	3.66	3.34	3.99	3.52
A17*	We have patient safety problems in this unit.	3.50	3.79	3.46	3.69	3.42
A18	Our procedures and systems are good at preventing errors from happening.	3.69	3.83	3.84	4.09	3.60
Feedback & Communication About Error**						
C1	We are given feedback about changes put into place based on event reports.	3.36	3.35	3.60	3.57	3.20
C3	We are informed about errors that happen in this unit.	3.81	3.87	3.99	4.03	3.54

C5	In this unit, we discuss ways to prevent errors from happening again.	3.83	4.00	4.14	4.19	3.79
	Communication Openness**					
C2	Staff will freely speak up if they see something that may negatively affect patient care.	3.76	3.76	3.76	3.71	3.39
C4	Staff feel free to question the decisions or actions of those with more authority.	2.96	2.93	2.78	2.52	2.80
C6*	Staff are afraid to ask questions when something does not seem right.	3.67	3.69	3.47	3.47	3.34
	Frequency of Events Reported**					
D1	When a mistake is made, but is caught and corrected before affecting the patient, how often is this reported?	3.30	3.77	3.74	3.85	3.58
D2	When a mistake is made, but has no potential to harm the patient, how often is this reported?	3.31	3.71	3.70	3.82	3.48
D3	When a mistake is made that could harm the patient, but does not, how often is this reported?	3.59	3.852	3.81	4.00	3.53
	Teamwork Across Units					
F2*	Hospital units do not coordinate well with each other.	2.94	3.13	3.42	3.26	3.21
F4	There is good cooperation among hospital units that need to work together.	3.45	3.52	3.67	3.80	3.48
F6*	It is often unpleasant to work with staff from other hospital units.	3.74	3.77	3.78	3.65	3.65
F10	Hospital units work well together to provide the best care for patients.	3.70	3.74	3.98	4.24	3.64
	Staffing					
A2	We have enough staff to handle the workload.	3.02	3.11	3.16	3.31	2.82
A5*	Staff in this unit work longer hours than is best for patient care.	2.73	2.71	2.51	2.24	2.43
A7*	We use more agency/temporary staff than is best for patient care.	3.66	3.34	3.17	2.86	3.31
A14 *	We work in “crisis mode” trying to do too much, too quickly.	2.92	2.82	2.68	2.74	2.79
	Handoffs & Transitions					
F3*	Things “fall between the cracks” when transferring patients from one unit to another.	3.64	3.53	3.63	3.83	3.39

F5*	Important patient care information is often lost during shift changes.	3.38	3.64	3.62	3.85	3.54
F7*	Problems often occur in the exchange of information across hospital units.	3.24	3.41	3.50	3.69	3.47
F11 *	Shift changes are problematic for patients in this hospital.	3.36	3.62	3.78	3.90	3.37
	Nonpunitive Response to Error					
A8*	Staff feel like their mistakes are held against them.	3.18	3.16	3.09	3.12	3.02
A12 *	When an event is reported, it feels like the person is being written up, not the problem.	3.00	3.10	3.03	2.83	2.85
A16 *	Staff worry that mistakes they make are kept in their personnel file.	2.82	3.03	2.77	2.46	2.84
	Sample size	222	2122	1786	230	874

** Items are negatively worded. Negatively worded items were reverse coded for analytic purposes.*
*** Items in these subscales anchored by Likert Scale where "1" is "Never," "2" is "Rarely," "3" is "Sometimes," "4" is "Most of the time," "5" is "Always"; all other items are anchored by on the same length Likert scale, but "1" is "Strongly Disagree," "2" is "Disagree," "3" is "Neither Agree nor Disagree," "4" is "Agree," "5" is "Strongly Agree."*

To see the description of the sampled survey respondents at the respondent level, see Table 1-2 in the Appendix. All descriptors were grouped by each of the five LatAm countries whose hospitals were surveyed for this study.

Confirmatory Factor Analyses (CFA)

CFA analyses results for the HSOPSC-R and HSOPSC-CS models are presented in Table 2. Recall that the HSOPSC-CS model outputs in Table 2 have one modification index applied to each of them, so the estimates shown inherently reflect calculations from a second, subsequently imposed CFA. The following is the breakdown of the model fit estimates of the base HSOPSC-R models versus the HSOPSC-CS, by country. Note that the only bootstrap 95% confidence intervals that did not overlap were with the country-data with the largest sample size – Chile (n = 2,122), which corresponded to the model fit estimates CFI [HSOPSC-R: (0.8557-0.8828); HSOPSC-CS: (0.9022-0.9264)], TLI [HSOPSC-R: (0.8350-0.8659); HSOPSC-CS: (0.8887-0.9163)], and SRMR [HSOPSC-R:

(0.0.602-0.0719); HSOPSC-CS: (0.0414-0.0493)]. Recall: higher measures above 0.9 are preferred for CFI and TLI and estimates lower than at least 0.08 are preferred for SRMR to deem that the models have adequate/good fit.

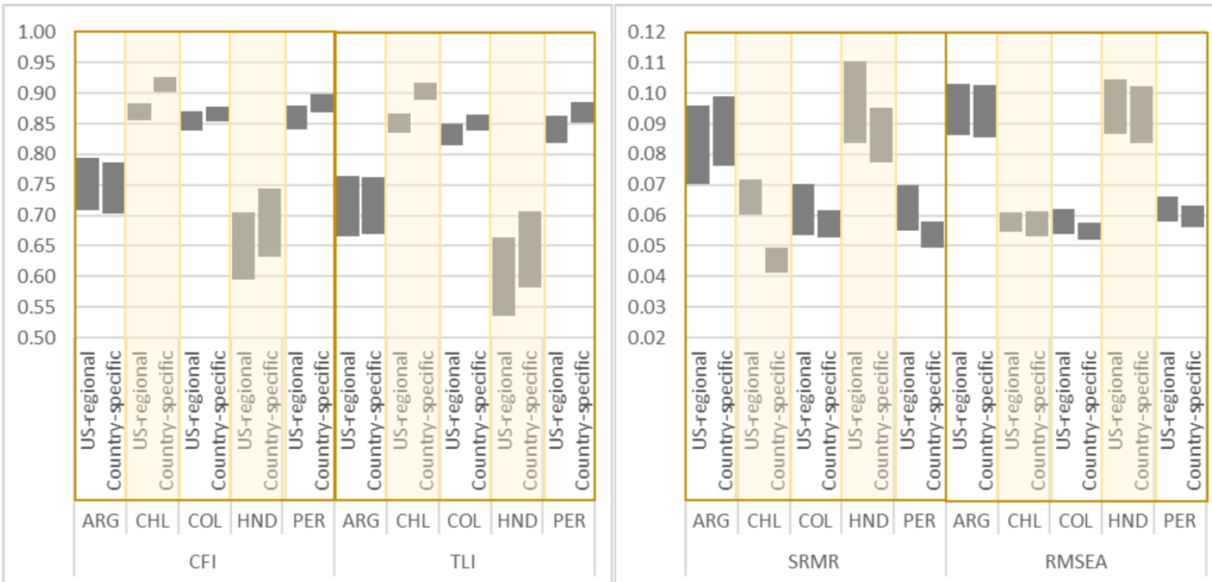
***Table 2*: Confirmatory Factor Analyses (CFA) on HSOPSC* across five Latin American countries**

Countries	**Argentina**		**Chile**		**Colombia**		**Honduras**		**Peru**	
***Fit Measures**	**R**	**CS**	**R**	**CS**	**R**	**CS**	**R**	**CS**	**R**	**CS**
Factor Model	12	10	12	9	12	8	12	11	12	9
# of Free Parameters	192	171	192	159	192	151	192	179	192	159
Overall χ^2	1,296.49	1,238.58	5,034.23	3,601.19	3,508.67	2,769.01	1,360.97	1,249.70	2,000.77	1,710.32
RMSEA	0.060 (0.086, 0.103)	0.060 (0.086, 0.103)	0.053 (0.052, 0.052)	0.052 (0.051, 0.051)	0.051 (0.054, 0.062)	0.047 (0.051, 0.057)	0.063 (0.087, 0.105)	0.058 (0.084, 0.102)	0.050 (0.058, 0.066)	0.047 (0.056, 0.063)
CFI	0.878 (0.708, 0.794)	0.878 (0.702, 0.787)	0.889 (0.856, 0.883)	0.929 (0.902, 0.926)	0.879 (0.838, 0.870)	0.904 (0.866, 0.889)	0.801 (0.594, 0.705)	0.844 (0.632, 0.743)	0.905 (0.841, 0.880)	0.924 (0.868, 0.897)
TLI	0.861 (0.666, 0.764)	0.865 (0.669, 0.763)	0.873 (0.835, 0.866)	0.920 (0.889, 0.916)	0.862 (0.815, 0.851)	0.894 (0.852, 0.878)	0.773 (0.536, 0.663)	0.822 (0.581, 0.708)	0.892 (0.819, 0.863)	0.916 (0.853, 0.886)
SRMR	0.065 (0.070, 0.096)	0.074 (0.076, 0.099)	0.064 (0.060, 0.072)	0.042 (0.041, 0.049)	0.056 (0.054, 0.070)	0.053 (0.052, 0.061)	0.082 (0.084, 0.111)	0.069 (0.077, 0.095)	0.058 (0.055, 0.070)	0.048 (0.050, 0.058)
Sample size	222		2,122		1,786		230		874	

** HSOPSC, Hospital Survey on Patient Safety Culture; R, HSOPSC regional model (HSOPSC-R); CS, HSOPSC Country-Specific models (HSOPSC-CS); df, degrees of freedom; AIC, Akaike's Information Criteria; BIC, Bayesian Information Criteria; RMSEA, Root Mean Square Error Approximation; CFI, Comparative Fit Index; TLI, Tucker-Lewis Index; SRMR, Standard Root Mean (Square) Residual; fit indices, observed coefficient, 1000-resampled bootstrap 95% confidence interval, percentile-corrected.*

A visual heuristic representation of the results of the bootstrap 95% confidence intervals of the CFA model fit indices can be seen below in Figure 1. It is subdivided into two sections: one covering the incremental fit indices (CFI and TLI), which bound them by the y-axis ceiling of 1.00 with a “higher-value-better” approach; the other section was the absolute fit indices – SRMR and RMSEA – with a y-axis ceiling of 0.12, with a “lesser-value-better” approach. All bar-graph intervals were grouped by each of the five LatAm countries, and within each country, there are two bars comparing each estimate for the HSOPSC-R and the HSOPSC-CS respectively. Recall that Chile is the country-data whose intervals do not overlap when placed side-by-side. The lengths of the bars vary, with longer lengths illustrating more variability in the estimates (hence a larger interval), and the opposite is true where smaller bars show less standard error in the estimates. These intervals are a function of sample size, with larger sampled country-data – Chile and Colombia – having smaller standard error variability bars than their other LatAm counterparts.

Figure 1. Bootstrap 95% Confidence Intervals of Confirmatory Factor Analyses Model Fit Indices



CFI=Comparative Fit Index. TLI=Tucker-Lewis Index. SRMR=Root Mean Square Error. SRMR=Standardized Root Mean Residual. ARG=Argentina (n=222). CHL=Chile (n=2,122). COL=Colombia (n=1,786). HND=Honduras (n=230). PER=Peru (n=874).

Reliability Analyses

Table 3 is divided into two sub-tables: the first is Table 3-1: HSOPSC-R model scales and Cronbach's Alpha estimates, by country; and the second is Table 3-2: HSOPSC-CS factor structure and Cronbach's Alpha measures, by country. The table shows the factor structure of the HSOPSC-CS models, and internal consistency measures for each composite by each respective country, while also presenting the Cronbach's Alpha estimates for the same base HSOPSC-R model that was imposed on each LatAm country. Below is a description of the HSOPSC-R scales (corresponding items within parentheticals) that made the Cronbach's Alpha cutoff value of greater than 0.7, by country (follow Table 3-1 for the full description).

Table 3: **HSOPSC-R & HSOPSC-CS model structure & internal consistency estimates**

Table 3-1: HSOPSC-R model scales and Cronbach's Alpha estimates, by country

HSOPSC-R Model Scales (Items)	Argentina	Chile	Colombia	Peru	Honduras
Teamwork Within Units (A1, A3, A4, A11)	0.765	0.694	0.651	0.755	0.765
Supervisor/Manager Expectations & Actions Promoting Patient Safety (B1, B2, B3,*, B4)*)	0.741	0.666	0.650	0.738	0.601
Organizational Learning - Continuous Improvement (A6, A9, A13)	0.763	0.735	0.694	0.649	0.689
Management Support for Patient Safety (F1, F8, F9)*)	0.729	0.707	0.645	0.665	0.567
Overall Perceptions of Patient Safety (A15, A18, A10,*, A17)*)	0.488	0.504	0.388	0.263	0.455
Feedback & Communication About Error (C1, C2, C3)	0.741	0.746	0.758	0.751	0.747
Communication Openness (C2, C4, C6)*)	0.697	0.547	0.580	0.584	0.542
Frequency of Events Reported (D1, D2, D3)	0.852	0.889	0.867	0.865	0.823
Teamwork Across Units (F4, F10, F2,*, F6)*)	0.813	0.699	0.680	0.689	0.643
Staffing (A2, A5,*, A7,*, A14)*)	0.265	0.362	0.272	0.309	-0.019
Handoffs & Transitions (F3,*, F5,*, F7,*, F11)*)	0.745	0.799	0.765	0.860	0.759
Nonpunitive Response to Error (A8, A12,*, A16)*)	0.668	0.524	0.615	0.59	0.398

**Items with "*" are negatively worded and therefore were reverse coded.*

Below is a description of the factor structure HSOPSC-CS models for each country, specifically those scales that made the Cronbach's Alpha cutoff of greater than 0.7, by country (follow Table 3-2 for the full description); note the item groupings within factors between the HSOPSC-R and HSOPSC-CS models.

Table 3-2: **HSOPSC-CS model's factor structure and Cronbach's Alpha estimates, by country**

Argentina	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Cronbach's Alpha
Fact1	A1	A3	A4						0.801
Fact2	*A5*	*A7*	*A10*	*A14*	*B3*				0.596
Fact3	A6	A9	A13	A15	A18				0.776
Fact4	*A8*	*A12*	*A16*						0.668
Fact5	B1	B2	*B4*						0.739
Fact6	C1	C2	C3	C4	C5	*C6*			0.822
Fact7	D1	D2	D3						0.852
Fact8	A2	A11	*F2*	F4	*F6*	*F7*	F10		0.836
Fact9	*F3*	*F5*	*F9*	*F11*					0.749
Fact10	*A17*	F1	F8						0.640

Removed

Chile	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Cronbach's Alpha
Fact1	A1	A3	A4						0.792
Fact2	A6	A9	A13	A15	A18				0.742
Fact3	*A8*	*A10*	*A12*	*A14*	*A17*	*B3*	*B4*	*C6*	0.758
Fact4	*F2*	*F3*	*F5*	*F6*	*F7*	*F11*			0.821
Fact5	B1	B2							0.816
Fact6	D1	D2	D3						0.889
Fact7	C1	C2	C3	C4	C5				0.774
Fact8	A2	F1	F8	*F9*	F10				0.733
Fact9	A11	F4							0.511
Removed	*A5*	*A7*	*A16*						

Colombia	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Cronbach's Alpha
Fact1	A1	A3	A4						0.726
Fact2	*A8*	*A10*	*A12*	*A14*	*A16*	*B3*	*B4*	*C6*	0.722
Fact3	A6	A9	A13						0.694
Fact4	*A17*	*F2*	*F3*	*F5*	*F6*	*F7*	*F9*	*F11*	0.812
Fact5	C1	C2	C3	C4	C5				0.773
Fact6	D1	D2	D3						0.867
Fact7	B1	B2							0.774
Fact8	A2	A15	A18	F1	F4	F8	F10		0.773
Removed	*A5*	*A7*	A11						

Honduras	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Cronbach's Alpha
Fact1	A1	A3	A4	*A5*	A6	A9	A11	A18	0.719
Fact2	*A8*	*A12*							0.685
Fact3	*A10*	*A14*							0.491
Fact4	C1	C2	C3	C5	F1				0.798
Fact5	*A17*	*B4*	*F3*	*F5*	*F6*	*F7*	*F9*	*F11*	0.817
Fact6	D1	D2	D3						0.823
Fact7	B1	B2							0.830
Fact8	A2	C4							0.370
Fact9	A16	C6							0.323
Fact10	A13	A15	*F2*	F8					0.502
Fact11	F4	F10							0.678
Removed	*A7*	*B3*							

Peru	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Cronbach's Alpha
Fact1	A1	A3	A4	A11					0.755
Fact2	*A8*	*A10*	*A12*	*A17*	*B3*				0.617
Fact3	A9	B1	B2						0.772
Fact4	*F2*	*F3*	*F5*	*F6*	*F7*	*F9*	*F11*		0.825
Fact5	D1	D2	D3						0.865

Fact6	*A14*	*B4*	*C6*			0.447
Fact7	C1	C2	C3	C4	C5	0.783
Fact8	A6	A13	A15	A18		0.694
Fact9	A2	F1	F4	F8	F10	0.778
Removed	*A5*	*A7*	*A16*			

**Italicized items were negatively worded, and therefore reverse-coded.*

Validity Analyses (Construct & Discriminant Validity)

To measure the construct validity and discriminant validity of the HSOPSC items, a combined inter-item correlation table was attempted, but was ultimately not included due to its sheer size, showing the Pearson correlation coefficients across the 42 items by all five LatAm countries in this study. Recall: inter-item correlations that are statistically significant, above a 0.300, and below a 0.800 ($\pm 0.300 \leq r \leq \pm 0.800$), maintain acceptable construct and discriminant validity, respectively. Considering the surfeit of all possible inter-item correlations across the 5 countries (8,610), below is a display of the survey items, by country, that did not meet the validity criteria above – for any bivariate correlation pairs between the other items.

Argentina's A5, A7, A16;
Chile's A5, A7, A16;
Colombia's A5, A7, A10, A14, A15, A16;
Honduras' A7, A16, B3;
Peru's A5, A7, A10, A16.

Note that items A5, A7, A10, A14, A16, and B3 are negatively worded and thus were reverse coded. The remaining HSOPSC items – too many items to list – either met all the criteria, or only partially met them, such as having a statistically significant bivariate correlations, but not within the criteria boundaries.

DISCUSSION

In this study, the Agency of Healthcare Research and Quality's (AHRQ) Hospital Survey on Patient Safety Culture (HSOPSC) – version 1 (2007) – was administered by hospital administrators from 32 hospitals across 5 Latin American (LatAm) countries. Using that survey data, tested the performance between the base HSOPSC – Regional model, which is the original Spanish-translated survey (2009) above versus country-specific models that we tailored to each respective LatAm country-data. This was done by employing factor analyses, interpretations of Pearson correlation matrices, and statistically-driven 95% bootstrap confidence interval comparisons of model fit indices. Ultimately, we found that 3 of 4 model fit indices were statistically significantly different for the Chilean country-data, whereas the remaining country-data model fit indices were not.

The results of this paper are consistent with those reported in the 2019 literature review of HSOPSC version 1 psychometric validation studies in various ways. Several of our findings matched those of the literature review mentioned above; however, the main two are reported below. The "Staffing" factor from the original regional model consistently had the lowest Cronbach's alpha estimates across all 5 LatAm country-data, and most of its items were consistently dropped from the country-specific models because of their poor performance. The items (A5, A7, and A14) from the Staffing factor are negatively-worded, which contributes to its poor psychometric performance.

The opposite is also true, with items D1, D2, and D3 from the "Frequency of Events Reported" factor, having Cronbach's Alpha all over 0.800, which is higher than the benchmark of 0.700. Though the results of each country's correlation matrices demonstrated that the Pearson correlations between the items demonstrated good discriminant validity, we found that the items in the "Frequency of Events Reported" factor were still too highly correlated. Also, the factor had universally high Cronbach's alpha estimates, with the smallest being 0.823 for both the regional and country-specific models across all 5 LatAm country-data. The biggest Cronbach's alpha value reported was 0.889. This is problematic because then the items by themselves do not uniquely contribute to the survey and could thus be dropped or reworded because of their redundancy. Again, this was another similar finding reported in the 2019 literature review.

Limitations

There were several limitations to this study that were addressed. First, varying sample sizes may affect the statistical significance of the results. Note that the bootstrap 95% confidence intervals that were not overlapped for three-fourths of the fit indices was the country-data from Chile, which had the highest sample size. Because of the participatory nature of this study, we could not control that the study data was collected voluntarily by strained, at-risk hospital staff during peak operation times. Still, the study results were statistically significant and were similar between sampled countries and across other studies from countries with different languages, cultures, and healthcare systems.

Though the sample was convenience-based, which could introduce some sampling bias, this limitation is acceptable considering the very complex nature and time constraints of the hospital staff that responded to the survey. Despite potential sampling bias, the bootstrap methods performed addressed some of these concerns. Bootstraps are designed to provide reproducible, automated calculations to be used for inferential statistics later. The pseudo-randomness aspect of the data resampling can help reduce statistical bias in the estimation of standard errors of the estimates provided. Also, bootstrap methods are reproducible when the seed value(s) is/are provided, eliminating statistical bias further.

Final Recommendations & Policy Implications

Concerning our final recommendation, though there is some evidence to suggest the benefit of tailoring surveys to their unique cultural, linguistic, and healthcare/hospital infrastructure contexts, we endorse the regional model for both its adequate model fit and the utility of being implemented across Latin America. While the country-specific model fit the Chile country-data better, it was not enough to justify more gains in psychometric validity and reliability to justify investing in tailored country-specific models for each LatAm Spanish-speaking country. Therefore, we support a regional model due to its potential for regional learning to improve patient safety across Latin America.

This paper supports the initiative of the World Health Organization's (WHO) 2021-2023 Global Patient Safety Action Plan to address patient safety culture (PSC)[4]. It also aligns with the National Academies' Committee on Improving the Quality of Health Care Globally (NACIQHCG) suggestion of using low-cost existing psychometrically validated measurement tools, instead of creating new ones that put a higher demand on already strained resources[1]. This paper can serve as evidence to inform policies within countries in LatAm that align with the WHO and the NACIQHCG. Practically-speaking, this paper serves as evidence to support administrators' decision to continue administering the regional HSOPSC version 1 in Spanish, unaltered, within their hospitals. Methodologically, this study identified improvement opportunities relevant for the next version of the HSOPSC (version 2)[37]. Currently, HMA at FIU survey and training methods are applied to Brazil, Chile, Colombia, and Peru. Our continued work, influence by the results of this study, will inform how we attempt to refine the version 2, Spanish-translated survey, using survey respondent data from staff working at hospitals within Latin American countries, including a Brazilian-Portuguese translation.

CONCLUSION

We conducted a psychometric validation study using secondary-data collected from volunteering hospitals within five LatAm countries (Argentina, Chile, Colombia, Honduras, and Peru). We attempted to validate the Spanish-translated Hospital Survey on Patient Safety Culture-Regional (HSOPSC-R) model. But in lieu of the resulting differences in dimensionality of the HSOPSC-R model across the five countries, we also built five HSOPSC-CS models for each country. We and ultimately assessed how well both models fit the country-data respectively and comparatively, their construct and discriminant validity, and internal consistency. Our results show that the though the HSOPSC-CS models fit the Chilean country-data better for 3 of 4 model fit indices, we found no statistically significant differences for all 4 model fit indices across the remaining 4 LatAm countries. Therefore, we ultimately recommend administrators to keep using the original HSOPSC Spanish-translated survey to measure patient safety culture within their hospitals, supporting the recommendations made by global health patient safety culture initiatives.

APPENDIX

***Table 1-1*: USA HSOPSC-R model structure & item-level descriptive statistics, by LatAm country**

		Argentina (*n* = 222)	**Chile (*n* = 2122)**	**Colombia (*n* = 1786)**	**Honduras (*n* = 230)**	**Peru (*n* = 874)**
Item	**HSOPSC-R Subscales & Descriptions**	**Mean(SD)** **SN(KS)^**	**Mean(SD)** **SN(KS)^**	**Mean(SD)** **SN(KS)^**	**Mean(SD)** **SN(KS)^**	**Mean(SD)** **SN(KS)^**
	Teamwork within Units					
A1	People support one another in this unit.	3.810(0.987) -1.054(0.929)	4.051(0.811) 1.058(1.206)	4.058(0.733) -1.264(2.228)	4.204(0.884) -1.514(2.484)	3.743(0.857) -1.029(0.987)
A3	When a lot of work needs to be done quickly, we work together as a team to get the work done.	3.937(0.762) -0.853(0.650)	3.996(0.866) -1.021(0.981)	3.952(0.719) -0.992(1.331)	4.184(0.949) -1.429(1.824)	3.697(0.895) -0.747(0.262)
A4	In this unit, people treat each other with respect.	4.018(0.964) -1.179(1.150)	4.284(0.709) -1.460(2.694)	4.221(0.555) -1.125(2.196)	4.245(0.814) -1.678(3.414)	3.869(0.790) -0.956(0.950)
A11	When one area in this unit gets really busy, others help out.	2.812(1.492) 0.091(-1.066)	3.000(1.613) -0.084(-1.141)	3.226(1.412) -0.366(-0.925)	3.581(1.597) -0.643(-0.687)	3.099(1.233) -0.261(-0.911)
	Supervisor/Manager Expectations & Actions Promoting Patient Safety					
B1	My supervisor/manager says a good word when he/she sees a job done according to established patient safety procedures.	3.467(1.240) -0.608(-0.329)	3.843(1.073) - 0.883(0.328)	3.728(1.034) -0.918(0.429)	3.877(1.257) - 0.896(-0.028)	3.591(1.154) -0.762(0.000)
B2	My supervisor/manager seriously considers staff suggestions for improving patient safety.	3.514(1.129) -0.742(0.030)	3.903(0.935) - 0.973(0.827)	3.806(0.876) -0.939(0.804)	3.890(1.173) - 0.863(0.061)	3.584(1.096) -0.806(0.133)
B3*	Whenever pressure builds up, my supervisor/manager wants us to work faster, even if it means taking shortcuts.	3.195(1.199) - 0.265(-0.745)	3.263(1.200) - 0.218(-0.722)	3.129(1.186) -0.212(-0.848)	3.058(1.302) 0.048(-0.908)	3.045(1.045) -0.096(-0.860)

B4*	My supervisor/manager overlooks patient safety problems that happen over and over.	3.833(1.296) -0.894(0.012)	4.063(1.038) - 1.104(0.740)	3.814(1.079) -1.006(0.569)	3.876(1.330) - 0.900(0.007)	3.695(1.032) -0.660(-0.170)
	Organizational Learning - Continuous Improvement					
A6	We are actively doing things to improve patient safety.	4.054(0.781) - 1.124(1.375)	4.109(0.705) - 1.063(1.551)	4.187(0.625) - 1.432(3.390)	4.367(0.756) - 1.898(4.142)	3.945(0.711) - 0.969(1.235)
A9	Mistakes have led to positive changes here.	3.786(0.868) - 0.947(0.863)	3.805(0.826) - 0.821(0.729)	3.891(0.738) -1.139(1.787)	4.044(0.884) - 1.100(1.154)	3.668(0.838) -0.921(0.742)
A13	After we make changes to improve patient safety, we evaluate their effectiveness.	3.559(1.056) - 0.825(0.216)	3.649(0.888) - 0.642(0.193)	3.898(0.745) -1.119(1.706)	4.000(0.890) - 1.165(1.395)	3.682(0.831) -0.885(0.632)
	Management Support for Patient Safety					
F1	Hospital management provides a work climate that promotes patient safety.	3.962(0.835) -1.172(1.715)	3.956(0.757) -0.989(1.303)	3.927(0.793) -1.036(1.296)	4.420(0.491) - 1.180(1.408)	3.636(0.897) - 0.775(0.307)
F8	The actions of hospital management show that patient safety is a top priority.	4.106(0.704) -1.037(1.331)	4.027(0.857) - 0.923(0.684)	4.117(0.705) -1.121(1.574)	4.391(0.789) - 1.685(2.848)	3.822(0.929) - 0.825(0.478)
F9*	Hospital management seems interested in patient safety only after an adverse event happens.	3.338(1.287) -0.352(-0.770)	3.420(1.384) -0.407(-0.810)	3.508(1.299) -0.637(-0.516)	3.487(1.675) - 0.553(-0.860)	3.227(1.166) - 0.172(-0.908)
	Overall Perceptions of Patient Safety					
A10*	It is just by chance that more serious mistakes don't happen around here.	3.555(1.174) - 0.548(-0.308)	3.593(1.198) - 0.469(-0.518)	3.254(1.190) -0.153(-0.827)	2.858(1.299) 0.243(-0.805)	3.142(1.103) 0.040(-0.855)
A15	Patient safety is never sacrificed to get more work done.	3.330(1.331) - 0.452(-0.677)	3.663(1.251) - 0.648(-0.353)	3.336(1.374) - 0.356(-0.915)	3.987(1.109) - 1.122(0.709)	3.519(1.156) - 0.557(-0.457)
A17*	We have patient safety problems in this unit.	3.502(1.200) - 0.402(-0.771)	3.785(1.168) - 0.767(-0.060)	3.463(1.230) - 0.519(-0.621)	3.692(1.544) - 0.696(-0.537)	3.424(1.139) - 0.398(-0.739)
A18	Our procedures and systems are good at preventing errors from happening.	3.685(0.755) - 0.682(0.552)	3.825(0.751) - 0.819(0.916)	3.842(0.719) - 1.040(1.500)	4.092(0.791) - 1.112(1.439)	3.599(0.888) - 0.822(0.475)
	Feedback & Communication About Error**					

C1	We are given feedback about changes put into place based on event reports.	3.355(1.367) -0.308(-0.714)	3.346(1.433) -0.319(-0.801)	3.596(1.264) -0.456(-0.542)	3.573(1.462) -0.511(-0.647)	3.204(1.301) -0.230(-0.638)
C3	We are informed about errors that happen in this unit.	3.808(1.076) -0.619(-0.369)	3.867(1.163) -0.836(0.074)	3.987(1.017) -0.839(0.109)	4.027(1.185) -0.896(-0.144)	3.536(1.191) -0.499(-0.344)
C5	In this unit, we discuss ways to prevent errors from happening again.	3.831(1.145) -0.764(0.012)	4.001(0.974) -0.879(0.280)	4.137(0.799) -0.912(0.480)	4.186(1.010) -1.163(0.761)	3.792(1.050) -0.710(0.108)
	Communication Openness**					
C2	Staff will freely speak up if they see something that may negatively affect patient care.	3.764(1.020) -0.725(0.292)	3.759(1.105) -0.654(-0.004)	3.756(1.036) -0.500(-0.337)	3.714(1.297) -0.623(-0.455)	3.390(1.248) -0.380(-0.580)
C4	Staff feel free to question the decisions or actions of those with more authority.	2.962(1.240) -0.008(-0.574)	2.931(1.218) -0.002(-0.628)	2.783(1.316) 0.157(-0.661)	2.522(1.418) 0.372(-0.700)	2.802(1.162) 0.054(-0.547)
C6*	Staff are afraid to ask questions when something does not seem right.	3.670(1.249) -0.581(-0.374)	3.688(1.130) -0.595(-0.163)	3.469(1.254) -0.344(-0.518)	3.473(1.462) -0.261(-0.932)	3.340(1.143) -0.243(-0.443)
	Frequency of Events Reported**					
D1	When a mistake is made, but is caught and corrected before affecting the patient, how often is this reported?	3.295(1.246) -0.148(-0.864)	3.767(1.268) -0.681(-0.382)	3.737(1.128) -0.487(-0.575)	3.845(1.281) -0.554(-0.971)	3.577(1.232) -0.332(-0.826)
D2	When a mistake is made, but has no potential to harm the patient, how often is this reported?	3.306(1.265) -0.158(-0.743)	3.708(1.277) -0.599(-0.514)	3.703(1.126) -0.403(-0.667)	3.819(1.317) -0.573(-0.744)	3.476(1.301) -0.270(-0.865)
D3	When a mistake is made that could harm the patient, but does not, how often is this reported?	3.589(1.266) -0.473(-0.536)	3.852(1.271) -0.815(-0.150)	3.808(1.123) -0.591(-0.436)	4.000(1.283) -0.877(-0.286)	3.531(1.382) -0.369(-0.867)
	Teamwork Across Units					
F2*	Hospital units do not coordinate well with each other.	2.942(1.093) -0.036(-0.466)	3.132(1.136) -0.143(-0.692)	3.415(1.048) -0.468(-0.435)	3.257(1.501) -0.209(-1.074)	3.209(0.878) -0.239(-0.615)
F4	There is good cooperation among hospital units that need to work together.	3.447(0.801) -0.632(0.175)	3.524(0.949) -0.565(-0.054)	3.667(0.798) -0.633(0.123)	3.796(1.021) -0.924(0.497)	3.482(0.710) -0.534(0.001)

F6*	It is often unpleasant to work with staff from other hospital units.	3.743(0.910) -0.777(0.490)	3.771(0.907) -0.637(0.201)	3.783(0.898) -0.765(0.335)	3.646(1.220) -0.707(-0.168)	3.654(0.789) -0.609(0.220)
F10	Hospital units work well together to provide the best care for patients.	3.700(0.876) -0.750(0.522)	3.742(0.808) -0.563(0.225)	3.977(0.705) -0.861(0.900)	4.239(0.704) -1.057(0.854)	3.638(0.826) -0.601(0.277)
	Staffing					
A2	We have enough staff to handle the workload.	3.018(1.198) -0.056(-1.07)	3.113(1.321) -0.130(-1.004)	3.157(1.312) -0.235(-1.015)	3.310(1.480) -0.231(-1.100)	2.824(1.167) 0.180(-1.013)
A5*	Staff in this unit work longer hours than is best for patient care.	2.731(1.110) 0.226(-0.694)	2.713(1.209) 0.219(-0.654)	2.507(1.126) 0.475(-0.530)	2.241(1.051) 0.823(0.227)	2.431(0.941) 0.597(-0.163)
A7*	We use more agency/temporary staff than is best for patient care.	3.659(1.088) -0.606(0.026)	3.342(1.105) -0.170(-0.495)	3.172(1.245) -0.114(-0.802)	2.860(1.264) 0.181(-0.678)	3.306(1.008) -0.153(-0.620)
A14*	We work in “crisis mode” trying to do too much, too quickly.	2.917(1.076) -0.082(-0.787)	2.819(1.186) 0.162(-0.705)	2.683(1.119) 0.288(-0.768)	2.744(1.195) 0.235(-0.673)	2.792(1.057) 0.244(-0.708)
	Handoffs & Transitions					
F3*	Things “fall between the cracks” when transferring patients from one unit to another.	3.636(0.814) -0.607(0.049)	3.530(1.180) -0.478(-0.528)	3.629(1.055) -0.676(-0.170)	3.827(1.148) -0.801(-0.069)	3.391(1.032) -0.364(-0.607)
F5*	Important patient care information is often lost during shift changes.	3.383(1.062) -0.392(-0.334)	3.638(1.026) -0.554(-0.204)	3.617(1.069) -0.608(-0.358)	3.845(1.078) -0.732(-0.245)	3.542(0.942) -0.388(-0.515)
F7*	Problems often occur in the exchange of information across hospital units.	3.238(1.055) -0.246(-0.581)	3.406(1.006) -0.248(-0.526)	3.499(0.936) -0.506(-0.298)	3.692(1.151) -0.710(-0.139)	3.465(0.796) -0.392(-0.390)
F11*	Shift changes are problematic for patients in this hospital.	3.357(1.003) -0.356(-0.418)	3.621(1.081) -0.475(-0.276)	3.784(0.981) -0.777(0.227)	3.898(1.233) -0.923(0.153)	3.369(1.033) -0.353(-0.472)
	Nonpunitive Response to Error					
A8*	Staff feel like their mistakes are held against them.	3.183(1.327) -0.217(-0.749)	3.160(1.211) -0.094(-0.737)	3.089(1.155) -0.107(-0.833)	3.115(1.273) -0.023(-0.726)	3.021(1.053) 0.061(-0.832)
A12*	When an event is reported, it feels like the person is being written up, not the problem.	2.995(1.475) -0.037(-0.988)	3.101(1.254) -0.067(-0.794)	3.033(1.295) -0.012(-1.022)	2.825(1.478) 0.236(-0.925)	2.853(1.056) 0.207(-0.840)

A16*	Staff worry that mistakes they make are kept in their personnel file.	2.816(1.072) 0.274(-0.398)	3.034(1.015) 0.045(-0.265)	2.768(1.128) 0.341(-0.646)	2.460(1.063) 0.495(-0.228)	2.836(0.960) 0.265(-0.627)

^ *SN, Skewness; KS, Kurtosis.*

** Items are negatively worded. Negatively worded items were reverse coded for analytic purposes.*

*** Items in these subscales anchored by Likert Scale where "1" is "Never," "2" is "Rarely," "3" is "Sometimes," "4" is "Most of the time," "5" is "Always"; all other items are anchored by on the same length Likert scale, but "1" is "Strongly Disagree," "2" is "Disagree," "3" is "Neither Agree nor Disagree," "4" is "Agree," "5" is "Strongly Agree."*

Table 1-2: **Hospital-level descriptive characteristics about respondents, by country (N=5855)**

Descriptor/Country (%) *	AR	AR%	CL	CL%	CO	CO%	HN	HN%	PE	PE%	Total	Total (%)*	Missing	Missing %
*Total Respondents**	231	3.95%	2160	36.9%	1922	32.8%	230	3.9%	1306	22.3%	5849	99.90%	6	0.10%
*Duration [MED; IQR (seconds)] **	1181	1439	1065	1109	1281	1215	1778.5	1215	1402	1639	1281		0	0.00%
Respondent Work Area/Unit	231	100%	2160	100%	1921	100%	230	100%	1306	100%	5848	99.88%	1	0.02%
Many different units/No specific	21	9.1%	157	7.3%	148	7.7%	19	8.3%	117	9.0%	462	7.89%		
Medicine (non-surgical)	24	10.4%	91	4.2%	154	8.0%	20	8.7%	171	13.1%	460	7.86%		
Surgery	3	1.3%	139	6.4%	101	5.3%	22	9.6%	110	8.4%	375	6.40%		
Obstetrics	12	5.2%	121	5.6%	104	5.4%	11	4.8%	15	1.1%	263	4.49%		
Pediatrics	10	4.3%	107	5.0%	143	7.4%	9	3.9%	25	1.9%	294	5.02%		
Emergency department	9	3.9%	94	4.4%	121	6.3%	15	6.5%	87	6.7%	326	5.57%		
Intensive care unit (any type)	33	14.3%	169	7.8%	188	9.8%	0	0.0%	25	1.9%	415	7.09%		
Psychiatry/mental health	1	0.4%	28	1.3%	18	0.9%	0	0.0%	7	0.5%	54	0.92%		
Rehabilitation	3	1.3%	94	4.4%	29	1.5%	6	2.6%	54	4.1%	186	3.18%		
Pharmacy	6	2.6%	31	1.4%	48	2.5%	6	2.6%	51	3.9%	142	2.43%		
Laboratory	6	2.6%	63	2.9%	65	3.4%	14	6.1%	67	5.1%	215	3.67%		
Radiology	3	1.3%	88	4.1%	33	1.7%	12	5.2%	20	1.5%	156	2.66%		
Anesthesiology	0	0.0%	28	1.3%	12	0.6%	2	0.9%	16	1.2%	58	0.99%		
Other	100	43.3%	950	44.0%	757	39.4%	94	40.9%	541	41.4%	2442	41.71%		
Overall work unit/area PSC grade	221	96%	2062	95%	1863	97%	228	99%	1255	96%	5629	96.14%	222	3.79%
A - Excellent	1	0.4%	5	0.2%	7	0.4%	0	0.0%	19	1.5%	32	0.55%		
B - Very Good	10	4.3%	63	2.9%	74	3.9%	5	2.2%	180	13.8%	332	5.67%		
C - Acceptable	88	38.1%	638	29.5%	480	25.0%	41	17.8%	604	46.2%	1851	31.61%		
D - Poor	108	46.8%	1053	48.8%	974	50.7%	81	35.2%	382	29.2%	2598	44.37%		
E - Failing	14	6.1%	303	14.0%	328	17.1%	101	43.9%	70	5.4%	816	13.94%		
Number of events reported	213	92%	1975	91%	1823	95%	225	98%	1216	93%	5452	93.12%	399	6.81%

No event reports	60	26.0%	1138	52.7%	816	42.5%	125	54.3%	580	44.4%	2719	46.44%		
1 to 2 event reports	60	26.0%	429	19.9%	481	25.0%	61	26.5%	353	27.0%	1384	23.64%		
3 to 5 event reports	53	22.9%	211	9.8%	254	13.2%	26	11.3%	146	11.2%	690	11.78%		
6 to 10 event reports	23	10.0%	103	4.8%	171	8.9%	8	3.5%	61	4.7%	366	6.25%		
11 to 20 event reports	12	5.2%	56	2.6%	65	3.4%	3	1.3%	36	2.8%	172	2.94%		
21 event reports or more	5	2.2%	38	1.8%	36	1.9%	2	0.9%	40	3.1%	121	2.07%		
Years worked in hospital	215	93%	1994	92%	1835	95%	228	99%	1227	94%	5499	93.92%	352	6.01%
Less than 1 year	21	9.1%	394	18.2%	302	15.7%	27	11.7%	148	11.3%	892	15.23%		
1 to 5 years	59	25.5%	782	36.2%	787	40.9%	87	37.8%	479	36.7%	2194	37.47%		
6 to 10 years	51	22.1%	364	16.9%	391	20.3%	46	20.0%	199	15.2%	1051	17.95%		
11 to 15 years	33	14.3%	162	7.5%	157	8.2%	51	22.2%	126	9.6%	529	9.04%		
16 to 20 years	11	4.8%	89	4.1%	75	3.9%	17	7.4%	113	8.7%	305	5.21%		
21 years or more	40	17.3%	203	9.4%	123	6.4%	0	0.0%	162	12.4%	528	9.02%		
Years worked in work area/unit	215	93%	1994	92%	1835	95%	228	99%	1227	94%	5499	93.92%	352	6.01%
Less than 1 year	29	12.6%	469	21.7%	460	23.9%	43	18.7%	222	17.0%	1223	20.89%		
1 to 5 years	75	32.5%	866	40.1%	896	46.6%	105	45.7%	571	43.7%	2513	42.92%		
6 to 10 years	46	19.9%	321	14.9%	275	14.3%	33	14.3%	210	16.1%	885	15.12%		
11 to 15 years	36	15.6%	145	6.7%	100	5.2%	34	14.8%	88	6.7%	403	6.88%		
16 to 20 years	6	2.6%	71	3.3%	46	2.4%	12	5.2%	63	4.8%	198	3.38%		
21 years or more	23	10.0%	122	5.6%	58	3.0%	1	0.4%	73	5.6%	277	4.73%		
Hours/week worked in hospital	215	93%	1994	92%	1835	95%	228	99%	1225	94%	5495	93.85%	356	6.08%
Less than 20 hours per week	11	4.8%	103	4.8%	51	2.7%	8	3.5%	29	2.2%	202	3.45%		
20 to 39 hours per week	93	40.3%	302	14.0%	229	11.9%	52	22.6%	665	50.9%	1341	22.90%		
40 to 59 hours per week	96	41.6%	1520	70.4%	1364	71.0%	140	60.9%	441	33.8%	3561	60.82%		
60 to 79 hours per week	8	3.5%	53	2.5%	139	7.2%	20	8.7%	40	3.1%	260	4.44%		
80 to 99 hours per week	6	2.6%	6	0.3%	31	1.6%	7	3.0%	17	1.3%	67	1.14%		
100 hours per week or more	1	0.4%	10	0.5%	21	1.1%	1	0.4%	31	2.4%	64	1.09%		

Staff position in hospital	215	93%	1994	92%	1835	95%	228	99%	1227	94%	5503	93.99%	352	6.01%
Registered Nurse	52	22.5%	320	14.8%	366	19.0%	54	23.5%	140	10.7%	934	15.95%		
Physician Assistant/Nurse Practitioner	38	16.5%	133	6.2%	173	9.0%	9	3.9%	117	9.0%	470	8.03%		
LVN/LPN	9	3.9%	6	0.3%	26	1.4%	3	1.3%	4	0.3%	48	0.82%		
PT Care Asst/Hospital Aide/CP	0	0.0%	14	0.6%	53	2.8%	2	0.9%	3	0.2%	72	1.23%		
Attending/Staff Physician	24	10.4%	280	13.0%	215	11.2%	12	5.2%	274	21.0%	806	13.77%		
Resident Physician/Trainee	5	2.2%	10	0.5%	16	0.8%	0	0.0%	36	2.8%	67	1.14%		
Pharmacist	7	3.0%	31	1.4%	41	2.1%	5	2.2%	24	1.8%	108	1.84%		
Dietician	1	0.4%	14	0.6%	5	0.3%	1	0.4%	9	0.7%	30	0.51%		
Unit Assistant/Clerk/Secretary	7	3.0%	117	5.4%	46	2.4%	19	8.3%	71	5.4%	260	4.44%		
Respiratory Therapist	1	0.4%	16	0.7%	7	0.4%	0	0.0%	3	0.2%	27	0.46%		
Physical/Occupational/Speech T.	1	0.4%	76	3.5%	19	1.0%	4	1.7%	38	2.9%	138	2.36%		
Technician (EKG, Lab, Radiology)	7	3.0%	143	6.6%	37	1.9%	15	6.5%	29	2.2%	231	3.95%		
Administration/Management	30	13.0%	235	10.9%	112	5.8%	34	14.8%	103	7.9%	514	8.78%		
Other	33	14.3%	599	27.7%	719	37.4%	70	30.4%	376	28.8%	1798	30.71%		
Direct Patient Contact?	215	93%	1994	92%	1835	95%	228	99%	1225	94%	5499	93.92%	356	6.08%
Yes	166	71.9%	1529	70.8%	1526	79.4%	181	78.7%	863	66.1%	4267	72.88%		
No	49	21.2%	465	21.5%	309	16.1%	47	20.4%	360	27.6%	1232	21.04%		
Years worked in profession	215	93%	1994	92%	1835	95%	228	99%	1226	94%	5502	93.97%	353	6.03%
Less than 1 year	13	5.6%	134	6.2%	152	7.9%	19	8.3%	62	4.7%	380	6.49%		
1 to 5 years	45	19.5%	563	26.1%	567	29.5%	85	37.0%	345	26.4%	1606	27.43%		
6 to 10 years	52	22.5%	461	21.3%	497	25.9%	42	18.3%	300	23.0%	1352	23.09%		
11 to 15 years	36	15.6%	274	12.7%	300	15.6%	45	19.6%	186	14.2%	841	14.36%		
16 to 20 years	18	7.8%	193	8.9%	135	7.0%	16	7.0%	145	11.1%	508	8.68%		
21 years or more	51	22.1%	369	17.1%	184	9.6%	21	9.1%	188	14.4%	815	13.92%		
Year of survey administration	231	100%	2160	100%	1922	100%	230	100%	1306	100%	5855	100.00%	0	0.00%

2018	9	3.9%	1416	65.6%	558	29.0%	0	0.0%	431	33.0%	2420	41.33%		
2019	0	0.0%	744	34.4%	677	35.2%	230	100%	873	66.8%	2524	43.11%		
2020	222	96.1%	0	0.0%	687	35.7%	0	0.0%	2	0.2%	911	15.56%		
Number of Hospitals	222	96%	2124	98%	1787	93%	230	100%	1306	100%	5669	96.82%	186	3.18%
1st	222	96.1%	285	13.2%	20	1.0%	230	100%	431	33.0%	1188	20.3%		
2nd			31	1.4%	150	7.8%			14	1.1%	195	3.3%		
3rd			112	5.2%	121	6.3%			121	9.3%	354	6.0%		
4th			75	3.5%	4	0.2%			43	3.3%	122	2.1%		
5th			250	11.6%	13	0.7%			695	53.2%	958	16.4%		
6th			113	5.2%	5	0.3%			2	0.2%	120	2.0%		
7th			298	13.8%	112	5.8%					410	7.0%		
8th			164	7.6%	253	13.2%					417	7.1%		
9th			52	2.4%	78	4.1%					130	2.2%		
10th			256	11.9%	346	18.0%					602	10.3%		
11th			245	11.3%	224	11.7%					469	8.0%		
12th			243	11.3%	245	12.7%					488	8.3%		
13th					216	11.2%					216	3.7%		

**Notes: Country (%), counts of number of respondents from each Latin American (LatAm) country followed by % of cases over grand total N = 5855. AR, Argentina; CL, Chile; CO, Colombia; HN, Honduras; PE, Perú. Total (%), percent of respondents over grand total N= 5855. Total Respondents, total number of respondents from each country which responded to survey; all response level counts based on country-specific totals, and same for their respective percents. Duration [MED; IQR (seconds)], median and inter-quartile range of survey administrations by country, median and IQR supplied because sampling distribution of survey administrations are skewed and kurtotic.*

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CHAPTER 2

ASSOCIATING HEALTH STATUS ATTRIBUTES to ACUTE-CARE USAGE in HIGH-NEED, HIGH-RISK VETERANS IN MIAMI

ABSTRACT

"High-Need, High-Risk" (HNHR) Veteran patients are identified quarterly by the Department of Veterans Affairs (VA) Geriatrics Extended Care Data Analysis Center (GECDAC) as having the top 5% probability of hospitalization or mortality. The Geriatrics, Research, Education, and Clinical Center (GRECC) designed and mailed a pilot survey to 2,543 Veterans identified as HNHR receiving care at the Miami VA Medical Center (VAMC) between October 2017 and September 2018, of which 634 replied. The survey contained 42 questions covering several health domains, with two acute-care utilization outcomes: 6-month prior emergency room stays (ERS), and inpatient hospital stays (IHS). Logistic regression was used to find factors that associated with both outcomes, and latent class analysis to group Veterans into clinically relevant latent classes. We found that the VA's Care Assessment Needs (CAN) Score (1-year) and issues with transportation to healthcare were associated with both outcomes. Self-perceptions of general health, and if a Veteran attended the frailty clinic at the Miami GRECC were associated with ERS and IHS, respectively. These results informed the development of the larger VA HNHR survey, identified non-clinical factors that affected acute-care usage, and a 4-class model grouped patients into distinct nominal latent classes that informed clinical recommendations.

Word Counts: 198
Key Terms: HNHR; GRECC; pilot survey; latent class analysis; logistic regression

INTRODUCTION

According to a 2023 Commonwealth report, hospital care is highest ranked factor affecting healthcare costs in the United States (U.S.), accounting for 31% of the market share, equaling to \$1.3T. When ranking patients from highest to least costly in terms of healthcare costs and usage, the top five percent costliest patients account for over 50% of the healthcare costs in the U.S. – a ten-fold differential[1]. Also, U.S. Veterans have poorer health statuses, utilize more healthcare resources, and have more clinical conditions than non-Veterans[2]. To curtail exacerbated acute-care usage, financial penalties for high readmissions were implemented, along with multicomponent interventions, and risk stratification models to identify patients with high probabilities of rehospitalizations[3]. Multicomponent interventions versus single-component interventions were stronger predictors of reducing hospital readmissions. In addition to severity of patients' illness and comorbidities, patient and caregiver goals of care were highly predictive of hospital readmission from a post-acute care (PAC) setting[4].

Multiple stakeholders have combined efforts to attempt to classify and better understand the high-needs patient population. Universities, health systems administrators, healthcare policy experts, clinicians, and researchers, to name a few, have created various definitions and terms to describe these patients. The Adults with Chronic Health Care Needs (ACHCN) definition identifies adult patients (18+) with at least 3 chronic healthcare conditions within the Medicare and Medicaid population[5]. The definition for "high utilizers" focuses on patients that are the highest healthcare resource utilization within the United States healthcare system[6]. Within the Centers for Medicare and Medicaid Services (CMS), "High-Cost, High-Need" patients are predominately women over 65 years old that have at least 2 chronic conditions and at least one indication of disability[7]. Comparing and contrasting these various definitions is beyond the scope of this study yet are relevant in highlighting how hard it is to identify these patients and get them the care they need.

The target population for this study is "High-Need, High-Risk" United States military Veterans. Using the Department of Veteran Affairs (VA) electronic medical records (EMR) system, the Geriatrics Extended Care Data Analysis Center (GECDAC) algorithmically identifies "High-Need, High-Risk" (HNHR) Veterans within the VA health system and ranks them from 0-99 based on the increasing probability of hospitalization or mortality. Those patients that are within the 95th through the 99th percentile are deemed HNHR, and become the targets of multimodal collaborative healthcare interventions, based off the VA's validated Care Assessment Needs (CAN) score. However, as robust as the VA's integrated EMR system is, there is a need to collect more and novel information about HNHR patients, to better serve their and their communities' needs[8].

Therefore, a survey was created to measure the healthcare needs of HNHR Veterans and their caregivers through a multi-site, multi-stakeholder collaboration. These included VAMC in Palo Alto, California, San Antonio, Texas, Salt Lake City, Utah, and Miami, Florida, and the Elizabeth Dole Center for Excellence in Veteran and Caregiver Research, to name a few investors. The purpose of this study was to analyze the pilot data of that survey in a cross-section of HNHR Veterans receiving care at the Miami VAMC, with the aims of identifying which survey elements predicted their acute-care usage. This study also assessed if these patients could be grouped into meaningful, evidence-based latent classes. In doing this, we wanted to see what were the clinically relevant distinguishing characteristics between the latent classes, approximately how many would fit into each, and which survey items are endorsed by patients' included into the latent classes.

METHODS

Instrument

The HNHR-658 pilot survey (Ruiz 2016) contained 42 questions. It was structured to encompass various domains/subject areas listed as follows: demographics, mental health, clinical health conditions, mobility, technology use, (access to and usage of) transportation, Caregiver status and social support system, physical function, (Instrumental) Activities of Daily Living (IADL & ADL respectively), and VA resource utilization. The health domains were all included to assess which aspects of health were significantly associated with the Veteran's acute-care utilization, and to help identify which survey items endorsed the Veteran's inclusion into their respective latent classes. The survey included single- and multi-selection multiple-choice questions, Likert-anchored items, and open-ended questions with short responses of no more than

100 characters, such as a self-reported indication of weight (in pounds) or questions identifying Caregiver(s), their name and relationship to the Veteran. All these items were self-reported from the Veteran's perspective. While the survey consisted of 42 main questions, there were many instances where questions had several subcomponents. These components could be categorized in three ways: some were study-specific, some were from pre-validated scales, and some were derived from an outside source. These outside sources originated from either the VA EMR data repository – the Corporate Data Warehouse (CDW) – or an external source.

Outcomes

The outcome measures for this study were the self-reported indications of all-cause emergency room stays (ERS) and all-cause hospital admittance (Inpatient Hospital Stays – IHS). They were expressed in the survey as separate items, preceded by "In the last 6 months:" and followed by "Have you gone to the emergency room for any reason" and "Have you been admitted to the hospital for any reason" measuring ERS and IHS, respectively. Both outcomes were dichotomously measured with options "Yes = 1" or "No = 0 (the reference category)." It is for this reason that binary logistic regression was used for the analyses of these outcomes – one regression equation per outcome. Because of the intrinsically nested nature of public health data, and the outcomes were categorical, a binary logistic generalized linear modeling approach was used for this study.

Categorical Predictors/Indicators

The following is a description of the main domains of questions asked, which are divided by categorical predictors with their response levels indicated, continuous predictors, and which ones were the demographic adjustors (which were a mixture of continuous or categorical variables). Regarding dichotomous categorical predictors, the "Fit Clinic" variable measured if the

Veteran patient had received care at the Miami VAMC that specifically focused on treating health-related indicators of frailty. It was recorded to measure attendance (Yes = 1, No = 0). Whether the Veteran had a recorded spinal cord injury was the final post-survey dichotomously measured variable measured in this study, (Yes = 1, No = 0).

Regarding categorically measured survey domains, homebound status was measured ordinally from 0-2 with values indicating either "not homebound," "semi-homebound," or "homebound" using questions from the already validated National Health and Aging Trends Study[4]. Other pre-validated categorical measures included in the survey was the screening result from the 2-item depression inventory – the Patient Health Questionnaire-2 (a two-item depression inventory[9]).

Questions assessing transportation-related health barriers were also asked. They covered issues related to transportation to a primary doctor, scheduling issues with doctor's appointments due to transportation, and duration of travel commute to doctors[10]. Categorical predictors that were study-specific revolved around two different domains. The first was regarding ambulatory movement measured through self-reported walking and balance issues, a count measure of falls in the past year, and if assistive devices to help with patient mobility were used. The other was technology use in relation to health, measured through self-reported technology usage of email, computer access and use, preferred method of contact, and questions regarding their account status with the VA patient portal platform "MyHealth*e*Vet."

Continuous Predictors/Indicators

The Continuous predictors measured in the study mainly consisted ordinally measured variables that had at least 5 response categories but were treated continuously[11]. For example, the interval variable that was treated continuously and was also auto-generated outside of the survey questions was the Area Deprivation Index – State Rank, ranging from 0-10 with higher values indicated more socioeconomically disadvantaged population densities[12]. Barthel's Activities of Daily Living (ADL) total score (interval ranging from 0-100 with higher scores meaning more independence) and Lawton's Instrumental Activities of Daily Living (IADL) total score (interval-level data ranging from 0-8 with higher scores indicating more independence) were measures of physical function[13-14].

The Care Assessment Needs (CAN) Score – (1-year) is an auto-generated VA measure of identifying Veterans receiving services within the VA based on their risk of hospitalization or morality, whereby it ranks them from lowest risk to highest risk. While the true ranked scores range from 0-99, this study's Veteran respondent's scores ranged from 40-99[15]. The risk assessment by the Centers for Medicare and Medicaid Services (CMS) – Hierarchical Condition Categories (HCC) – was also auto-generated outside of the survey. Its questions were measured as interval-level data ranging from 0-15, with higher scores indicating worse health in terms of the risk adjustment of frailty, costs of treatment, multiple, comorbid chronic conditions, mental illness, and morbidity[16].

The JEN Frailty Index (JFI) Score [An all-providers healthcare claims-based score that measures the risk of being admitted to a nursing home for prolonged stay[17] (also correlated to Medicare & Medicaid expenditures and mortality) that uses nearly 1,800 diagnoses across 13 condition categories significantly associated with concurrent and future long-term care services: minor/severe ambulatory limitations, cognitive developmental disability, chronic mental illness, dementia, sensory disorders, self-care impairment, syncope, cancer[18]. Finally, the NOSOS Score was another auto-generated continuous predictor in the survey using the Centers for Medicare & Medicaid (CMS) Hierarchical Condition Categories (HCC) risk adjustment model, it uses the following: age, gender, ICD-9/10 diagnoses, pharmacy and VA priority status and computed costs (to name a few) – it is used to model the total annual VA cost for each patient on predicted risk scores[19].

Other predictors revolved around self-reported physical health status. Survey questions asking Veterans “when was the last time you felt at your best, physically,” ranging from 0 – “I felt at my best now” through a score of 4 “it’s been more than 5 years than I’m not felt at my best physically.” Another question in the same physical health domain was about general health: “In general, how would you rate your health today – please select one,” from an interval of responses ranging from 0 “Very Bad” to 4 “Very Good.”

The Social Network Index (SNI) Score [using Berkman & Syme’s validated Social Network Index (SNI) items], was used to assess the social network dynamics of patient’s health. The total score is aggregated using four questions: “in a typical week, how many times do you talk on the telephone with family, friends, or neighbors,” “how often do you get together with friends or relatives,” “how often do you attend church or religious services,” “how often do you attend meetings of the clubs or organizations you belong to.” All items are Likert-based with at most 5-6 response levels each, and this scale is designed to measure the size of the social network, closeness of its members within it, and frequency of contact, which was found to predict mortality independent of socioeconomic status. It is interval data – again treated continuously –with a range between 0-4, with higher values indicating stronger social networks[20].

In a 2004 study in the United States, researchers found in relation to caregiving and social networks higher weekly time commitments – despite employment status and commitments – to informal care for a parent or spouse, was associated with increased depression symptomology in women that had them, versus those without them. Conversely, women with higher social ties had more favorable health outcomes[21]. Similarly, a 2019 study conducted in Spain found that the size and types of social networks are important in relation to feeling of loneliness and depression among older adults. This was especially true for women between the ages of 50-65 that were widowed, divorced, or single, with a lower level of education, and medium household income that lived in rural areas; yet could be addressed by increasing the social interactions and communication skills[22].

The Self-Perception of Aging (SPA) Score [a total score measuring the latent factor of self-perceptions of aging (SPA)] uses the following 5 questions from Miche et al.'s Attitude Toward Own Aging (ATOA) subscale as follows: "things keep getting worse as I get older," "I have as much pep as I did last year," "the older I get, the more useless I feel," "I am as happy now as I was when I was younger," "as I get older, things are better than I thought they would be," which are all anchored on a Likert scale ranging from 1-6, with 1 being "strongly disagree" through 6 being "strongly agree"; the total score was aggregated from the sum of scores for each item, not the Likert-based response given by the survey respondent, meaning whether there was an indication of agreement (Y = 1) or rejection (Y = 0) of the perception of their aging, with items 2, 4, and 5 reverse-coded so that higher scores indicated a more positive attitude towards their individual aging journey[23]. A 2021 systematic literature review found that higher SPA scores was related to positive, longitudinal health outcomes such as better self-rated health, less obesity, greater longevity, better performance on scores measuring independence, less depression, and better cognitive functions[24].

We measured Veterans Affairs (VA) resource utilization as an aggregate of the following available services. These were measured by the question "Do you receive any of the following services – select all that apply" included the following resources used:

Assisted Living Facility, Aid and attendance, Adult-Day Healthcare, Caregivers support group, Community Health Nurse, Community Living Center, Community Nursing Home, Home-Based Primary Care (HBPC) programs Home Health Aide, Home Telehealth, Meals on Wheels, Medical Foster Home, Program of All-Inclusive Care for the Elderly (PACE), Palliative Care/Hospice, Respite Care (home or institutional), State Veteran Home, VA Video Connect, Veteran Directed Care.

This interval variable was treated continuously, with a range between 0-17, with higher values indicating more VA resource utilization by Veteran patient.

For this study, the usual demographic indicators were measured and considered model adjustors; in other words, if any of these predictors were statistically significant during the analyses phase, then the experimental models would be compared with and without adjusting for demographic covariates and factors. There were several patient-level demographic qualities measured. Postal (Zip) Codes were recorded nominally for most patients. Race and Ethnicity were measured dichotomously, as “White, Non-Hispanic” versus “Non-White, Non-Hispanic” for race, and “Hispanic or Latino,” versus “Not Hispanic or Latino,” for ethnicity, respectively. Marital Status was not adjusted directly as it is a component of the Social Network Index described above. Yet, it was measured dichotomously as “married” or “unmarried” for this study. Educational Attainment was measured ordinally, anchored on an eight-item Likert scale with the following ranged values:

0 = “No Schooling completed,” 1 = “Elementary school to 8th grade,” 2 = “Some high school, no diploma,” 3 = “Highschool graduate, diploma, or equivalent,” 4 =

"Some college credit, no degree," 5 = "Associate degree," 6 = "Bachelor's degree," 7 = "Master's degree," 8 = "Professional/Doctorate degree."

Health Literacy was measured using the singular question "How confident are you filing medical forms by yourself – please select one" that was bound ordinally with a range of 1-5, starting with 1 being "not confident," 3 being "somewhat confident," and ending with 5 "very confident"; the question was modeled after Chew et al.'s study[25].

Data Cleaning & Analytic Dataset Creation

After the data cleaning and creation of the analytic dataset was performed using Excel 2019[26], the assumption of multicollinearity was checked by calculating the Variance Inflation Factor[27] for each predictor, along with descriptive statistics of person-level and item-level characteristics that encompasses mean and standard deviations for continuous predictors, and sample size and complete-case percentages for categorical predictors. Preliminary chi-square crosstabulations (either as Fisher's Exact Tests, regular Chi-Squared, or Likelihood Ratio Tests, depending on if assumptions were kept or violated) and two-sample t-tests were performed to compare categorical and continuous predictors against each of the dichotomously measured outcomes, respectively. These were performed as univariate unadjusted testing of which predictors would be meaningful to include in the binary logistic regression models to come. Because the nature of the data originated from a pilot study, and the sampled participants represent a special health sub-population of patients with complex needs and clinical/psychosocial comorbidities, missingness was expected beforehand. So, statistical significance was considered acceptable at an alpha level of $\alpha = 0.10$. Table 0 in the Appendix illustrates the survey structure, item-level descriptive statistics, and the VIF multicollinearity assessment measure.

Logistic Regression

We performed two main multivariable binary logistic models to regress on the outcome variables. The first was considered "Model 1" and is interchangeably referred to as the "Full Model." It is an unadjusted (meaning the model did not regress person-level demographic qualities of the sampled patients), complete-case analysis (only participants with full data on all variables were included in the model), for each outcome. The inclusion criteria for the variables in these equations were if during the univariate testing, the predictors were statistically significantly and dependently associated with either outcome at the $\alpha = 0.10$ mentioned earlier. Table 2 shows the logistic regression model testing the multivariable associations for both outcomes on a mixture of categorical and continuous predictors, using a generalized linear modeling approach. The processes to create the second main model were more involved.

After the full binary logistic models were run, it was noted that the apparent missingness in the data lowered the statistical power of the models considerably, because the analytic sample sizes for each outcome dropped by nearly 50% each. Missing value analyses were performed comparing the missingness of each of the previous Full Model's predictors to each outcome, presenting the present cases and percents, and the missing percents for each predictor in Model 2. Table 3 presents the univariate missingness of both outcomes across covariates and factors, and by illustrating these estimates, and rank-ordering the predictors based on the highest-to-lowest missing percent. These missing value analyses influenced the decision to find the best-fitting model by backwards stepwise selection, using an empirical variable selection procedure of removing predictors in the order of the least statistically significant, and keeping those that were. Then, the binary logistic regression with the remaining predictors were rerun, also using a generalized linear modeling approach, achieving a final parsimonious (smallest, best-fitting) model.

All the model-fit estimates, in some capacity, measure if the study models we created are performing well enough to be used to meaningfully associate aspects of health with our intended outcomes. As aforementioned, the model inclusion criteria for predictors to be in the Full Model were that they were statistically significant having beyond an observed significance level of $\alpha = 0.10$, and to not be multicollinear; however, an extra two conditions were imposed on predictors to be in the Parsimonious Models for each outcome. One condition was for each variable to have less than 10% missing data on either level of the binary response outcome, for each outcome. The other condition was that these variables were already a part of the preceding Full Model.

Model fit estimates were calculated for both Model 1 – the Full Model – and Model 2 – the Parsimonious Model. Table 4 displays several estimates. It includes the Akaike and Bayesian information criteria, which could be compared heuristically through the "smaller-better" approach. It also includes the -2 log likelihoods with degrees of freedom that were used to perform the likelihood ratio test that compared the nested parsimonious model fit to the model fit of the larger, full model. The Hosmer and Lemeshow goodness of fit test, and the Omnibus Tests of Model Coefficients were both included. The latter had two purposes: It displayed if the final stepwise procedure in this variable selection process significantly contributed to the final model; And if the final model was statistically significantly different when compared to "Model 0 – the intercept-only model (with no predictors, just the outcome)." SPSS version 28 was the statistical software used for this study[28].

The model fit behavior was assessed between both models across both outcomes; in total four models were being compared. Model 1 was divided into two full generalized linear models (GLM), one for each binary outcome (hence the method binary logistic generalized linear modeling). For this paper, the distinction for these models will be designated Model 1 – Outcome

1 and Model 1 – Outcome 2. Model 2 was divided into two parsimonious GLM models, one for each outcome; Model 2 – Outcome 1, and Model 2 – Outcome 2. Therefore, there are four models of interest. The model fit statistics that were used as comparative model-selection metrics are listed, followed by a description of what they represent. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) formulas both involve the regression components of the Sum of Squares Errors (*SSE*), the sample size (*n*), and the number of parameters measured (*k*), and only differ by a (k + 1) parameter.

They are used together to compare model fit, whereby the model with the lower value is considered better fitting. Note: the BIC measure favors more parsimonious (smaller models with less parameters that are all at least statistically significant and/or significantly contribute to the model) models because it penalizes models with higher number of parameters (k + 1)[29]. -2 log-likelihood (-2LL statistic – also known as "the deviance measure") indicates how much unexplained variation there is in the logistic regression model by comparing the difference between the predicted versus actual outcome across each case, then summing them for a total measure of the error in the model (similar yet not quite as the information criteria do above. Therefore, the compared model with a smaller deviance statistic is also deemed the "better fitting" model[30].

The Hosmer and Lemeshow goodness of fit test (HL test) was also used to compare model fit. It is a goodness of fit chi-squared (χ^2) test for binary logistic models that tests against the null hypothesis that the model fits the data well, with an alternative hypothesis that the model does not fit the data well[31]. The Omnibus Tests of Model Coefficients (OTMC) is a stepwise test against the null model and each subsequent model thereafter. If the "Step" phase is statistically significant, that implies that the next step in the stepwise regression was a statistically significant improvement from the prior model, whereby in SPSS the original Step 1 procedure is compared to an implied

“Step 0” meaning just the intercept model. For this study, backwards stepwise elimination was used to calculate, find, and regress the parsimonious model – more on the parsimonious model later. If the “Model” phase is statistically significant, this implies that the combination of all the predictors for that step’s model are statistically significant in comparison to the null model (intercept only).

Essentially, much like the HL test, the OTMC also follows a chi-square distribution, but ultimately they test different hypotheses, according to David Morse on ResearchGate, who says that the HL test evaluates whether the model performance is homogeneous/internally congruent throughout the range of continuous predictors, versus the overall model tests evaluates whether the reduction in log-likelihood, when compared to the null/intercept-only model, relative to the degrees of freedom, is statistically significant[32].

Table 5 includes the parsimonious model for each outcome using backward stepwise (likelihood ratio) selection binary logistic regression, with an empirical variable selection strategy, a generalized linear modeling approach, and complete case analyses. Basically, to create the parsimonious model, we started with the Full Model (all the significant predictors from the variable screening process illustrated in Table 1), and had SPSS rank all the predictors based off of p-values (observed significance levels that determine if a predictor is significantly associated with the outcome or not) from highest to lowest values (range between 0.000 – 1.000), and at every step, eliminate them one-by-one backwards. Backwards implies taking the least statistically significant item from the model, removing it, and rerunning this process iteratively until all the predictors involved are statistically significant and the model fit statistics show that this last step model fits the data the best, i.e., backwards stepwise. Regarding the participants involved, the models included participant data with no missing values for both outcomes (complete case analysis), until only the smallest group of statistically significant predictors remained (parsimonious model). Therefore, Table 5 shows the parsimonious model and presents the summary statistics, Wald χ^2 test statistics with their observed significance levels, odds ratios and the 95% confidence intervals that bind those odds ratios[33].

Latent Class Analyses

To compare this pilot survey results to the larger Veterans Affairs HERO Care survey, latent class analyses (a dimension reduction technique) were performed to assess the following research sub-questions: are there different latent classes of HNHR Veteran patients based on their responses to the survey items; what is the relative proportion of inclusion into these latent classes; what qualitative descriptions best describe the latent classes that these patients could fall into; and, what non-clinical recommendations can we give towards targeting interventions to address the unmet needs, health statuses, or latent class profiles these patients fall into? See Table 6 in the Appendix for the breakdown.

To answer these questions, a series of sub-analyses were done in the following procedural order. Determining what latent class model fits the data the best was the first step, and to assess model fit, the following model fit indices were calculated: Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), and sample-size-adjusted Bayesian Information Criteria (aBIC) were calculated and compared on the premise that a smaller value would indicate better fit (sans direct statistical/computational comparisons, just visually). The observed significance level (p-value) for the Lo-Mendell-Rubin (LMR) Adjusted Likelihood Ratio Test, and that of the Parametric Bootstrapped Likelihood Ratio Test comparing null (previous) versus alternative (current) models were calculated, where the metric of comparison was statistical non-significance between the models, suggesting a more complex model would not fit better than its preceding latent class model – where the opposite is also true. To answer the proportion of patient-latent class inclusion, the counts and percents of latent class inclusion were provided based on the likely latent class membership approach.

Once the latent class model was established, the patient-centered latent class endorsement estimates (sub-grouped by survey items, their descriptions, and classes) were provided, using the probability of inclusion scale. Meaning, the survey items included that were recoded dichotomously to reflect Y = 1 (has negative trait) versus Y = 0 (does not have negative trait) were cross tabulated against the latent classes found, to see the traits that are endorsed by the patients who fit into certain latent classes. The metric of comparison to establish which items belonged to which latent class was when the probability value was at least higher than 0.500 (50%), the highest of the probabilities between all the latent classes, and if there was a tie for the two or three highest probabilities that differed by about less than 0.05 (5%), both items were said to be endorsed by each latent class.

Because these clinical concepts are multidimensional and highly intercorrelated at best, if two or probability estimates differed by a rough, nonempirically established difference of 0.05 from the highest estimate, then that item was considered to be a quality that is also representative of the patients that fell into other latent classes as well. Note: it is of utmost importance to emphasize now the power and importance of the practical, real-world interpretability of the latent classes. Along with statistically accurate and precise estimates that suggest which is the best fitting latent class model and its structure, especially when it comes to patient-centered data and recommended interventions, it is equally relevant to consider their practically and clinical relevance.

Finally, once the probability scale estimates were calculated, a meaningful interpretation of the items being endorsed by patients for each respective latent class, and thus descriptions of these nominal latent classes are created, which could serve as a basis for meaningful targeted interventions based on which latent classes patients fall into. To qualitatively, conceptually, and meaningfully extrapolate proper nomenclature to describe and name the latent classes, and what patients belong to them, latent class descriptions were attributed to them based on a theoretical basis of how the survey items would interrelate to build the latent class, but also some understanding of the survey respondent population – HNHR Veterans localized in Miami, Florida. See Table 6 in the Appendix for these estimates, which were calculated using MPLUS version 8.5[34].

Data Collection

2,543 Veterans receiving care at the Bruce W. Carter Miami Veteran Affairs Medical Center (VAMC) were identified by the GECDAC to be HNHR between October 2017 and September 2018. 1,300 were randomly selected to receive the survey, where the first part was through the United States Postal Service in May 2018, with the remaining sample being sent the survey in November of 2018. An additional 173 HNHR Veterans that were also scheduled for geriatric frailty clinical appointments localized near the Miami VAMC completed the survey too; 71 and 102 were in-person and phone respectively. The response rate was 35.5%, with a total of 461 survey respondents returning the questionnaires via mail, plus 173 that participated in-person or via a phone call, totaling the sample to 634[35].

RESULTS

The following section below only includes statistically significant tests and predictor results, for the sake of space. Please refer to the full tables in the Appendix for the full illustration and the presented scope of statistical procedures performed.

Preliminary Crosstabulations

Preliminary crosstabulations of the categorical predictors found the following predictors were significantly associated and dependent on the emergency room stays outcome: Fit Clinic [*Fisher's Exact Test*(*df*) = 4.663(1); *p-value* = 0.035], Postal (Zip) Code [*Likelihood Ratio Test*(*df*) = 137.442(115); *p-value* = 0.068], PHQ2 Screening Score [*Fisher's Exact Test*(*df*) = 3.402(1); *p-value* = 0.076], Transportation [χ^2(*df*) = 14.469(3); *p-value* = 0.002), Scheduling [*Fisher's Exact Test*(*df*)= 5.439(1), *p-value* = 0.024], and Email [*Fisher's Exact Test*(*df*) = 3.196(1); *p-value* = 0.081]. The preliminary crosstabulations of the categorical predictors on the second outcome (inpatient hospital stays) found the following predictors statistically significant: Fit Clinic [*Fisher's Exact Test*(*df*) = 23.554(1); *p-value* < 0.001], Has Prosthetics [*Likelihood Ratio Test*(*df*) = 12.023(5); *p-value* = 0.034], Transportation [χ^2(*df*) = 11.992(3); *p-value* = 0.007], and Scheduling [*Fisher's Exact Test*(*df*) = 3.085(1); *p-value* = 0.097]; see Table 1-1 for the tabulated results of the summary statistics and univariate comparisons of associations between both outcomes and categorical predictors; see Table 1-1 for further details.

Preliminary two-sample samples *t*-tests of the continuous predictors found the following predictors to be significantly associated and dependent on the emergency room stays outcome: Care Assessment Needs (CAN) Score 1-year [*t*(*df*) = -4.359(240.983); p-value < 0.001], Falls (Count) [*t*(*df*) = -3.587(412.415); *p-value* < 0.001], General Health [*t*(*df*) = 3.282(643); *p-value* < 0.001], Chronic Health Conditions (HCC) [*t*(*df*) = -2.273(645); *p-value* = 0.023], HNHR Group (Count) [*t*(*df*) = -2.347(645); *p-value* = 0.019], and Physical Status [*t*(*df*) = 1.958(632); *p-value* =

0.051]. Preliminary independent samples *t*-tests of the continuous predictors found the following predictors to be statistically significantly associated and dependent on the second outcome – inpatient hospital stays: Activities of Daily Living (ADL) Score [$t(df)$ = 2.418(543); *p-value* = 0.016], CAN Score 1-year [$t(df)$ = -3.051(610); *p-value* = 0.002], Falls (Count) [$t(df)$ = -1.972(615); *p-value* = 0.049], General Health [$t(df)$ = 2.923(620); *p-value* = 0.004], Chronic Health Conditions (HCC) [$t(df)$ = 1.667(622); *p-value* = 0.096], HNHR Group (Count) [$t(df)$ = 2.786(622); *p-value* = 0.005], Instrumental Activities of Daily Living (IADL) Score [$t(df)$ = 1.593(584); *p-value* = 0.062], Physical Status [$t(df)$ = 1.912(610); *p-value* = 0.056], Self-Perceptions of Aging (SPA) Score [$t(df)$ = 2.348(585); *p-value* = 0.019]; see Table 1-2 for the summary statistics and univariate comparisons of associations between both outcomes and continuous predictors; see Table 1-2 for more details.

Logistic Regression – Full Models

These are the statistical estimates from the logistic regression model testing multivariable associations for both outcomes (Outcome 1 first, then Outcome 2) across the mixture of categorical and continuous predictors that were statistically significant from the crosstabs and *t*-tests mentioned above. For the sake of uniformity, comparability, and to estimate the most robust and valid model with the given data possible, if one of the variables was statistically significant on one of the outcomes, that predictor was regressed on both outcomes. For Outcome 1, the total sample of complete-cases was n = 383 (59% of 649), with 262 (68% of 383) Veteran patients reporting that "Yes" (Y = 1), they have gone to the emergency room for any reason within the past 6 months, and 121 (32% of 383) reporting that "No," (Y = 0), they were have not gone to the emergency room for any reason within the past 6 months. For Outcome 2, the total sample of complete-cases was n = 369 (59% of 626), with 251 (68% of 369) Veteran patients reporting that "Yes" (Y = 1), they have been admitted to the hospital for any reason within the past 6 months, and 118 (32% of 369) that responded "No" (Y = 0), they had not been admitted to the hospital for any reason within the past 6 months.

The categorical predictors that were statistically significant on the 6-month self-reported all-cause emergency room stays (ERS) reported by the Veteran were as follows: the intercept for the model [*Wald* χ^2 = 6.182; *p-value* = 0.013, *odds ratio* (*OR*) = 0.01; 95% *confidence interval* (*CI*) *OR* = (0.000, 0.374)], having a prosthetic, specifically a cane (Y = 1) [frequency of cases *n(%)Wald* χ^2 = 4.068; *p-value* = 0.044; OR = 0.532; 95% CI OR = (0.288, 0.982)], having "a lot of trouble" (Y = 3) with Transportation [*Wald* χ^2 = 3.244; *p-value* = 0.072; OR = 3.666; 95% CI OR = (0.892, 15.070)]. The continuous predictors that were statistically significant on Outcome 1 were as follows: Care Assessment Needs (CAN) Score 1-year [*Mean*(*Standard Deviation*) = $\bar{x}(s)$ = 92.52(8.245); *Wald* χ^2 = 13.737; *p-value* < 0.001; OR = 1.066; 95% CI OR = (1.030, 1.102)], Falls (Count) [$\bar{x}(s)$ = 1.80(1.946); *Wald* χ^2 = 6.222; *p-value* = 0.013; OR = 1.202; 95% CI OR = (1.040, 1.389)], General Health [$\bar{x}(s)$ = 1.96(.907); *Wald* χ^2 = 5.602; *p-value* = 0.018; OR = 0.635; 95% CI OR = (0.436, 0.925)].

The categorical predictors that were statistically significant on the 6-month self-reported all-cause inpatient hospital stays (IHS) reported by the Veteran were as follows: being seen (Y = 1) at the Fit Clinic [*n(%)* = 98(27%); *Wald* χ^2 = 10.189; *p-value* = 0.001, *odds ratio* (*OR*) = 0.425; 95% *confidence interval* (*CI*) *OR* = (0.251, 0.719)], using a wheelchair (Y = 5) most often from the choices given [n(%) = 32(9%); *Wald* χ^2 = 4.591; *p-value* = 0.032, *odds ratio* (*OR*) = 0.287; 95% *confidence interval* (*CI*) *OR* = (0.092, 0.899)], having "a lot" of trouble with Transportation [n(%) = 27(7%); *Wald* χ^2 = 3.518; *p-value* = 0.061, *odds ratio* (*OR*) = 4.727; 95% *confidence interval* (*CI*) *OR* = (0.933, 23.931)].

The continuous predictors that were statistically significant on the 6-month self-reported all-cause emergency room stays (ERS) reported by the Veteran survey respondent were as follows: the Care Assessment Needs (CAN) score (1-year measure) [range = (40-99); $\bar{x}(s)$ = 92.52(8.245); *Wald* χ^2 = 13.737; *p-value* < 0.001, *odds ratio* (*OR*) = 1.066; 95% *confidence interval* (*CI*) *OR* = (1.030, 1.102)], the number of times they have fallen in the past year [Falls (Count): range = (0-6); $\bar{x}(s)$ = 1.80(1.946); *Wald* χ^2 = 6.222; *p-value* = 0.013, *odds ratio* (*OR*) = 1.202; 95% *confidence interval* (*CI*) *OR* = (1.040, 1.389)], the general rating of their health on the day they took the survey [General Health: range = (0-4); $\bar{x}(s)$ = 1.96(0.907); *Wald* χ^2 = 5.602; *p-value* = 0.018, *odds ratio* (*OR*) = 0.635; 95% *confidence interval* (*CI*) *OR* = (0.436, 0.925)]. The continuous predictor that was statistically significant on the 6-month self-reported all-cause inpatient hospital stay (IHS) reported by the Veteran survey respondent was also the CAN score (1-year measure) [range = (40-99), $\bar{x}(s)$ = 92.46.80(8.284); *Wald* χ^2 = 3.072; *p-value* = 0.080, *odds ratio* (*OR*) = 1.027; 95% *confidence interval* (*CI*) *OR* = (0.997, 1.059)]; see Table 2 for further details.

As part of the model building process to create the Parsimonious Model, an extra step was to look more closely at the missingness in the variables that made it into the Full Model. Upon further inspection, it was found that these variables had missingness that was over 10% for Outcome 1 (in increasing order of missingness): Instrumental Activities of Daily Living (IADL) [Total = 9.9%; "Yes" (Y = 1) = 9.0%; "No" (Y = 0) = 11.3%], Activities of Daily Living (ADL) [Total = 12.8%; "Yes" (Y = 1) = 13.4%; "No" (Y = 0) = 10.3%], Email [Total = 23.1%; "Yes" (Y = 1) = 23.6%; "No" (Y = 0) = 21.5%]. Also, the same variables also had high levels of missingness in Outcome 2 (in increasing order of missingness): Instrumental Activities of Daily Living (IADL) [Total = 9.9%; "Yes" (Y = 1) = 10.1%; "No" (Y = 0) = 9.5%], Activities of Daily Living (ADL) [Total = 12.8%; "Yes" (Y = 1) = 14.7%; "No" (Y = 0) = 8.9%], Email [Total = 23.1%; "Yes" (Y

= 1) = 22.7%; “No” (Y = 0) = 22.6%] – See Table 3 for a further breakdown of missing data of the Full Model across the outcome measures.

Model Fit – Full versus Parsimonious Model Fit

Table 4 presents the model fit estimates from both full and parsimonious binary logistic regression models, for both outcomes. Overall, the parsimonious model fit better than the full model – as expected – for both Outcome 1 [Full Model: *AIC* = 473.32, *BIC* = 560.18, *-2LL* = -214.66; Parsimonious Model: *AIC* = 299.97, *BIC* = 326.65, *-2LL* = -143.99] and Outcome 2 [Full Model: *AIC* = 462.94, *BIC* = 548.98, *-2LL* = -209.47; Parsimonious Model: *AIC* = 365.27, *BIC* = 396.11, *-2LL* = -175.63]. When it comes to the logistic regression model fit comparison, the Full model for Outcome 1 [HL test: $\chi^2_{df} = 1.97(1)$; p-value = 0.98], the Full model for Outcome 2 [HL test: $\chi^2_{df} = 3.76(8)$; p-value = 0.88], and the Parsimonious models for Outcome 1 [HL test (Step 13): $\chi^2_{df} = 8.47(1)$; p-value = 0.39] and Outcome 2 [HL test (Step 12): $\chi^2_{df} = 10.96(8)$; p-value = 0.20] all passed the Hosmer and Lemeshow Test (HL Test).

Regarding the stepwise process, the Omnibus Tests of Model Coefficients were performed for all four models. Both the Step 1 Full Model phase for Outcome 1 [Step 1: $\chi^2_{df} = 48.48(21)$; p-value < 0.001] and Outcome 2 [Step 1: $\chi^2_{df} = 43.57(21)$; p-value = 0.003] were statistically significant. Again, these statistics mean that each Full Model was significantly better than the null “Step 0” model, meaning just the intercept only, without any predictors, hence that at least some of the predictors meaningfully explained each respective outcome. When it came to the backward elimination stepwise process, the first outcome had 13 steps [Step 13: $\chi^2_{df} = -2.37(1)$; p-value = 0.124], and the second outcome had 12 steps [Step 12: $\chi^2_{df} = -1.86(1)$; p-value = 0.172], which may seem insignificant because both statistical estimates were non-statistically significant; however, both the final model for Outcome 1 [Model 13: $\chi^2_{df} = 33.47(5)$; p-value < 0.001] and the final model for Outcome 2 [Model 12: $\chi^2_{df} = 30.51(6)$; p-value < 0.001] were both statistically significant when compared to the null models. Recall: the HL tests for each final step of the Parsimonious Models were non-significant, meaning that both those logistic models fit well.

Logistic Regression – Parsimonious Model

Because Table 5 includes the results for the Parsimonious Model, based on the explanation above, almost all of the predictors involved would be statistically significant across both outcomes. The results for Outcome 1 [self-reported Emergency Room Stays (ERS) within the past 6 months] demonstrated that the intercept [*Wald* χ^2_{df} = 10.978(1); *p-value* < 0.001, *odds ratio* (*OR*) = 0.023; 95% *confidence interval* (*CI*) *OR* = (0.002, 0.214)], the CAN Score (1-year) [*range* = (40-99); $\bar{x}(s)$ = 93.23(7.683); *Wald* χ^2_{df} = 19.819(1); *p-value* < 0.001, *odds ratio* (*OR*) = 1.054; 95% *confidence interval* (*CI*) *OR* = (1.030, 1.079)], the Veteran patient's General Health [*range* = (0-4); $\bar{x}(s)$ = 1.90(0.909); Wald χ^2_{df} = 4.235(1); p-value = 0.04, odds ratio (OR) = 0.806; 95% confidence interval (CI) OR = (0.656, 0.990)], the Veteran patient's Transportation situation when they have "Some Trouble" [*X* = 2; *n(%)* = 85(13.5%); *Wald* χ^2_{df} = 2.845(1); *p-value* = 0.092, *odds ratio* (*OR*) = 1.666; 95% *confidence interval* (*CI*) *OR* = (0.921, 3.015)] and when they report having "A Lot of Trouble" [*X* = 3; *n(%)* = 57(9.0%); *Wald* χ^2_{df} = 6.101(1); *p-value* = 0.014, *odds ratio* (*OR*) = 2.980; 95% *confidence interval* (*CI*) *OR* = (1.253, 7.089)].

Despite the intercept of the regression model for the first outcome being statistically significant, the intercept for Outcome 2 [self-reported Inpatient Hospital Stays (IHS) within the past 6 months (Y = 1)] was not [*Wald* χ^2_{df} = 2.456(1); *p-value* = 0.117, *odds ratio* (*OR*) = 0.168; 95% *confidence interval* (*CI*) *OR* = (0.018, 1.562)], and so was the General Health measure [*range* = (0-4); $\bar{x}(s)$ = 1.91(0.916); *Wald* χ^2_{df}= 2.198(1); *p-value* = 0.138, *odds ratio* (*OR*) = 0.849; 95% *confidence interval* (*CI*) *OR* = (0.684, 1.054)]; however, the CAN Score (1-year) was once more statistically significant [$\bar{x}(s)$ = 93.25(7.588); *Wald* χ^2_{df} = 7.639(1); *p-value* = 0.006, *odds ratio* (*OR*) = 1.033; 95% *confidence interval* (*CI*) *OR* = (1.010, 1.058)]. Transportation was also statistically significant when Veteran patient's reported having "A Lot of Trouble" getting transportation to their primary doctors [*X* = 3; *n*(%) = 53(8.7%); *Wald* χ^2_{df} = 6.740(1); *p-value* = 0.009, *odds ratio* (*OR*) = 3.330; 95% *confidence interval* (*CI*) *OR* = (1.343, 8.256)]. "Being seen" or getting a clinical evaluation after the survey at the Miami Veteran Affairs Medical Center (VAMC) "Fit Clinic" at the Miami Geriatrics, Research, Education, and Clinical Center (GRECC) was also a statistically significant predictor of Outcome 2 [*X* = 1; *n*(%) = 146(24.1%); *Wald* χ^2_{df} = 16.866(1); *p-value* < 0.001, *odds ratio* (*OR*) = 0.435; 95% *confidence interval* (*CI*) *OR* = (0.293, 0.647)].

The odds of a Veteran patient being admitted to an emergency room within the past 6 months ($Y_1 = 1$) while having a cane (X = 1) as their assistive device of choice that they use most often is about 46.8% odds lower than not using an assistive device (X = 0). If this survey were replicated 100 times, 95 of these survey administrations would find the true population odds for a Veteran patient being admitted to the emergency room within the past 6 months that used a cane, when compared to not using an assistive device, was between the interval of 71.2% and 1.8% decrease in odds. A similar pattern is observed when Veterans use a wheelchair.

The odds of a Veteran patient being admitted to an emergency room within the past 6 months ($Y_1 = 1$) while using a wheelchair (X = 5) as their most often used assistive device is about 1.5% decrease in odds than not using an assistive device (X = 0). If this survey were replicated 100 times, 95 of these survey administrations would contain the true population odds for a Veteran patient being admitted to the emergency room within the past 6 months that used a wheelchair, when compared to not using an assistive device, was between the interval of a 72% decrease in odds and a 2.93-fold increase in the odds – a potential ceiling of nearly 3 times the odds! A similar occurrence is observed when Veterans use a wheelchair.

The odds of a Veteran patient being having an inpatient stay at a hospital within the past 6 months ($Y_2 = 1$) while using a wheelchair (X = 5) as their most often used assistive device is about 71.3% decrease in odds than not using an assistive device (X = 0). If this survey were replicated 100 times, 95 of these survey administrations would contain the true population odds for a Veteran patient having an inpatient stay within the past 6 months that used a wheelchair, when compared to not using an assistive device, was between the interval of a 90.8% and a 10.1% decrease in odds.

The odds of a Veteran patient having an emergency room (ER) stay (ERS) within the past 6 months ($Y_1 = 1$) while having had a fall in the past year [range = (0-6) with 0 = "No falls," and 6 = "six or more"] is associated with an 20.2% increase in odds of being admitted to the ER. If the survey were replicated 100 times, 95 of these survey administrations would contain the true population odds for a Veteran patient having an ERS within the past 6 months that had a fall, and that interval would be between a 4% to 38.9% increase in the odds of being admitted.

While these predictors were both statistically significant at an $\alpha = 0.10$, the following interpretations are based off the Parsimonious Models for each outcome, respectively, as to avoid redundant explanations of significance and relevance. Regarding emergency room stays (ERS), the intercept of both regression models (Full and Parsimonious) was statistically significant. The implication behind the intercept being statistically significant means there could have been variables unaccounted for by model that could have significantly explained variation in Emergency Room Stays, therefore while the models fit the data well and overall were statistically significant, future work could improve upon potential limitations of this study, by perhaps addressing completeness of data and statistical power using different methods. In terms of odds, predictors associated with the variation unaccounted for by the regression model account for a 91.7% decrease in odds of ERS, with a 95% confidence interval of the decrease in odds ranging from a 99.8% to a 78.6% decrease in the odds of a Veteran patient having an emergency department (ED) evaluation.

The CAN Score (1-year) measure had a 5.5% increase in odds per one unit increase in the score (recall the range of the scores for this study was between 40-99), with a 95% confidence interval of odds increase from 3% to 7.9% increase in the odds per one unit increase in the CAN Score. The results of this study add to existing research that validates the CAN Score as a predictive tool for predicting risk of hospitalization or death among primary care receiving Veterans within the Veterans Health Administration (VHA)[11].

The odds of a Veteran patient self-reporting being admitted to an emergency room within the past 6 months decrease by 19.4% odds per one unit increase on the Likert-based survey item "In general, how would you rate your health today – please select one?" Out of 100 survey administration replications, 95 of them would contain the true population odds of a Veteran patient being evaluated by a hospital's emergency department between the interval 34.4% to 1% decrease in odds. The implications behind these results are great – listening to Veterans about their complaints and self-perceived health statuses, despite their clinical comorbidities, is very important, as they themselves are the best indicators of their health and if they are (un)well.

The odds of a Veteran patient self-reporting being admitted to an emergency room within the past 6 months were associated by a 67% increase in odds, with a 95% confidence interval of odds hovering around a 7.9% decrease in odds and a 301.5% increase in odds (a three-fold increase) when reporting having "Some Trouble" when asked "how much trouble is it for you to get transportation to your primary doctors?" The odds of a Veteran patient self-reporting being admitted to an emergency room within the past 6 months were associated by a 298% increase in odds (almost three-fold), with a 95% confidence interval of odds hovering around a 25.3% increase in odds and a 709.9% increase in odds (a seven-fold increase) when reporting having “A Lot of Trouble” when asked the same question Transportation question above.

While the intercept was not statistically significant for both models regressed on Outcome 2, this implies a strength of the model building design in that the model explained sufficient variation in inpatient hospital stays of these Veteran patients. The unexplained variation in inpatient stays encompassed by the intercept (null model) was statistically non-significant, meaning, the predictors involved in the model sufficiently explained the having an inpatient hospital stay, therefore highlighting in this case that the study had no missing variable bias for that outcome. The CAN Score (1-year) measure had a 3.3% increase in odds per one unit increase in the score, with a 95% confidence interval of the true population odds increase from 1% to 5.8% increase in the odds per one unit increase in the CAN Score. Again, this is important in that the CAN Score (1-year) can not only predict ERS but also IHS too, adding to the literature showing the efficacy of the measure within the Veteran’s Health Administration health system.

Once again, not having consistent access to primary care doctors can exacerbate hospitalization and delay the discharge of Veteran patients. The odds of a Veteran patient having an inpatient hospital stay while reporting having “A Lot of Trouble” when asked “how much trouble is it for you to get transportation to your primary doctors” is associated with a 333% increase in odds (a three and a third-fold increase), with a 95% confidence interval of the true population of odds bound between a 34.3% and an 825.6% increase in odds (almost 8 times as likely to be hospitalized when reporting having “A Lot of Trouble”).

The odds of a Veteran HNHR patient being hospitalized within the past 6 months are associated with a 56.5% decrease in odds when they were seen at the FIT clinic at the Miami Veterans Affairs Medical Center (VAMC). The 95% confidence interval of the true population of odds may be represented by a 35.3% to a 70.7% decrease in odds by being seen at the FIT Clinic. The role of the Fit Clinic for Veterans after hospitalization may deter them from returning to the hospital because they are receiving the care they needed but follow up was not provided through this study and therefore not included as part of this study.

Latent Class Analyses

After a series of latent class analyses, the latent class model that fit the data the best was the 4-class model [AIC = 29,778.99; BIC = 30,659.54; aBIC = 30,027.75; p(LMR) = 0.0098; p(Bootstrap) < 0.0000]. The patient class counts and proportions based on likely latent class membership was n_1 = 69(11%), n_2 = 188(30%), n_3 = 224(36%), n_4 = 136(22%) for latent classes one through four, respectively. The survey items that are endorsed by HNHR Veteran patients that fit into latent class 1 (called HNHR-A) include items the domains below.

Frail Scale about "feeling tired" (0.723), "difficulty walking up steps" (0.954), "difficulty walking without aids" (0.968).

Social Network Index about "telephoning with others" (0.625), "getting together with others" (0.828), "attending religious services" (0.917), "attending meetings/clubs" (0.903).

Physical health/functioning such as a patients' "general health rating" (0.598), having "issues with walking and balance" (0.941), "having a fall" (0.817), "not feeling their best physically" (0.557), "having exercise barriers" (0.839), "not having or having used a pedometer" (0.982), "no interest in receiving a pedometer from the VA" (0.513).

Barthel's Activities of Daily Living (ADL) items covering "feeding" (0.733), "bathing" (0.787), "grooming" (0.764), "dressing" (0.938), "bowels" (0.733), "bladder" (0.823), "toilet use" (0.832), "transfers" (0.824), "mobility" (0.823), and issues "climbing stairs" (0.965).

Lawton's Instrumental Activities of Daily Living (IADL), including issues with "shopping" (1.000), "food preparation" (1.000) "housekeeping" (0.710), "laundry" (0.969), "issues with modality of transportation" (0.815), "medication adherence issues" (0.908), "handling finances" (0.574).

Technology use includes "non-modern preferred methods of contact" (0.571), "having a computer and able to go on the internet and perform a search" (0.681).

Self-perceptions of aging scale covering perceptions that "things are worse the older they got" (0.822), "they do not have the same pep in their step as they once had" (0.784), "feeling useless as they got older" (0.773), "unhappier now as ever" (0.796), and perceiving that "things are worse as they got older" (0.811).

The survey items that are endorsed by HNHR Veteran patients that fit into latent class 2 (called HNHR-B) include items from the domains below.

Frail Scale about having "difficulty walking up steps" (0.901), "difficulty walking without aids" (0.899).

Social Network Index, one item covering "getting together with others" (0.787).

Physical health/function covering various items that include "issues with walking and balance" (0.967), "having a fall" (0.834), "having not felt their best physically" (0.554), "having exercise barriers" (0.759).

Barthel's ADLs, one item describing "issues with climbing stairs" (0.734).

Lawton's IADLs, items covering issues with "shopping" (0.872) and "food preparation" (0.842).

Self-perception of aging, all but one item including "things are worse the older they got" (0.822), "they do not have the same pep in their step as they once had" (0.757), "unhappier now as ever" (0.799), and perceiving that "things are worse as they got older" (0.791).

The survey items that are endorsed by HNHR Veteran patients that fit into latent class 3 (called HNHR-C) include items from the following domains:

Dimensions of caregiving such as "not having a caregiver" (0.843).

Social Network Index by the item describing "not being married" (0.606).

Physical health/function such as "not feeling their best, physically" (0.505).

Self-perceptions of aging items that include "feeling worse as they got older" (0.818), "as unhappy now as before" (0.737) and perceiving that "things are worse as they got older" (0.713).

Finally, the survey items that are endorsed by HNHR Veteran patients that fit into latent class 4 (called HNHR-D) include items from the domains below.

Dimensions of caregiving, meaning "not having a caregiver" (0.870).

Social Network Index by the item "not being married" (0.592).

Physical health/function measured by the items describing "having a poor physical status rating" (0.782)

Patient Health Questionnaire (PHQ) depression screen, highlighting that the patient screened “positive” for depression (0.957).

DISCUSSION

The way the question is worded in the survey, there is an ordinal relationship between an implied level of physical frailty in the choice of assistive device most used by the Veteran patient, with the reference category being not using a device, the next ordinal level being a cane, and the final level being using a wheelchair, with the former implying more robust maneuverability by the patient that is ambulatory with a cane versus the opposite implication when the patient’s most used assistive device is a wheelchair – the last level in the directional question. This could be why the next statistically significant predictor in the Full Model being described below was a self-reported count of falls within the past year – “how many times have you fallen in the past year?”

Falls in the literature of HNHR Veteran patients are statistically associated with ER visits, and our findings align with research showing how falls affect patient health[31]. A systematic literature review and meta-analysis of 3 included studies about emergency department (ED) history, physical examination, and fall risk stratification instruments mentioned that falls are the leading cause of traumatic mortality in geriatric adults[36]. The authors, Carpenter et al. also found among these studies that a self-report of depression was associated with the highest positive likelihood ratio for falls in geriatric patients in the past 6 months of an ED evaluation, along with six significant fall predictors, including living alone (social isolation), a history of falls, using assistive devices, mental health indicators like depression and cognitive deficits, and polypharmacy – more than six medications[36].

While there is a dearth of studies analyzing the effectiveness of assistive devices including frail older adults, sans clear standards to guide professionals, older users and their relatives, this study adds to that literature because all these patients are Veteran patients with a high risk of hospitalization or mortality [(High-Need, High-Risk (HNHR)]. Certain assistive devices were found to successfully predict hospitalization in this study sample, and this matches what was found in other studies[37]. According to a systematic literature review by Fotteler et al (2022), the use of assistive technology is designed to enable seniors to be more independent at home or in residential facilities, and improve their quality of life by addressing age-related difficulties, yet they also found that studies including participants with significant or severe impairment showed no effectiveness with the use of assistive devices, while grouping patients using frailty indicators from measures such as the ones in this study – Barthel's Activities of Daily Living (ADL) and Lawton's Instrumental Activities of Daily Living (IADL).

It would appear that when these HNHR patients get admitted, they receive multiple services, along with a full evaluation, instead of specifically identified, targeted care for a particular ailment; however, because of the complex, interconnected, and comorbid health profiles of these patients, perhaps they need prolonged hospital stays to fully diagnose the condition that brought them there in the first place, to stabilize their vitals – which takes longer the older and more infirm a patient is. Nevertheless, this may then translate to exacerbated acute-care utilization, and even the patients' transition to institutionalization and more long-term care outside their communities.

The latent classes we discovered add an extra layer of identifying Veteran patients that are High-Need, High-Risk. So far, the VA can identify and risk-stratify the patients that have the highest probability of hospitalization or mortality, but the results of this study help the VA identify the services these patients need. The latent classes were divided into 4 categories, HNHR-A through HNHR-D.

Based off the latent class analyses above, qualitatively and non-clinically speaking, it appears that the HNHR Veteran patients that seem to most likely fit in latent class HNHR-A have a Caregiver and are married, present the following qualities in a major way: physical function issues, frailty and dependence, poor self-perceptions of aging, social network deficits, and technology use deficits. They are receiving care at home, have fallen, and are uniquely characterized by having a caregiver, being married, and having the highest need for healthcare, attention, and socialization.

The HNHR Veterans from Miami that seem to fit into the latent class HNHR-B depicts qualities such as having no Caregiver and being unmarried, having minor mobility difficulties and uses assistive devices, having moderately poor self-perceptions of aging and physical status rating, and have fallen. While they are still ambulatory, they need assistive devices, despite having fallen, and are uniquely characterized by no socialization outside the home, yet not bed ridden.

Respectively, Veterans in latent class HNHR-C have no Caregiver and are unmarried, have fallen, and have minorly poor self-perceptions of aging and physical status rating. While they are still ambulatory and social, they are uniquely characterized by having fallen. Finally, for the fourth latent class, HNHR-D, these Miami Veterans show signs of depression, have no Caregiver and are unmarried, have minorly poor physical self-rating and movement. They are still ambulatory, social outside the home, have not fallen, and are uniquely characterized by their mental health deficits – primarily depression.

Strengths

The following is a list of a few strengths of the study design. There was sufficient statistical power by adding the parsimonious model approach that was aided by complete case analyses. This study is an example of the integration of prospective survey data acquisition followed by post-study auto-generated variables working together to meaningfully extrapolate real-world actionable results for the VA. As such, the external validity of these results may be extrapolated to other Veterans receiving care in Miami, let alone South Florida, regionally speaking, and perhaps Veterans that share similar matched demographics that share geographical and culture similarities to Florida. The results of this study lead to actionable latent classes that these HNHR Veterans from Miami could fall into, identifiable by unique characteristics, to the extent that they could inform targeted interventions to further enhance the quality of care, in combination with the prediction algorithms in place to identify and rank them.

Limitations

It is important to know that many other predictors could have been statistically significant for both outcomes and could be very associated with indicators of physical frailty such as (Instrumental) Activities of Daily Living, and other dimensions of health. But all of these were not included because they were negatively affected by missing data. These variables would be more statistically significantly associated with their respective outcomes had there been more complete data. Missing data imputation was considered and ultimately not implemented because the Full larger survey data exists (the HERO Care survey), which was greater in overall scope of sample size, geographical outreach, topics covered, and measured longitudinally – more about this work in the sequel dissertation paper following this one.

The following is a list of a few limitations to the validity of the results, but also ways that they were addressed and/or their effects mitigated within the study. Multicollinearity of the various aggregated scales that were used because they consisted of composites with multiple variables that sometimes overlapped; however, this was addressed through calculating the Variance Inflation Factors of each variable, to which end none of them were above a value of 10 – the cutoff point.

Measurement invariance could be speculated to be a problem with this work having multiple questions having various Likert-based scales; however, this was addressed by repeated modeling techniques and filtering processes to find the variables measured in their best capacity, reaching the most patient respondents. This was also addressed by using predictors that encapsulated the totaled, scaled, screened, or scored versions of the assessments, rather than the varying items by themselves that comprised the measures. Finally, this problem was addressed in the latent class analyses phase of the study because the involved variables were dichotomized, hence having uniform response categories throughout the modeling process.

Temporal directionality of the outcomes came before the survey measurement, and treatments came after, so the directionality of association is not traditionally forward – though it is seemingly linear because of the modeling. This was addressed with the entire time horizon of the HNHR-658 as a pilot study with the HERO Care survey coming after this survey, to show that these predictors are statistically significantly associated with both outcomes.

Generalizability of the results extrapolate to mainly High-Need, High-Risk Veteran patients living within the State of Florida for the HNHR-658 pilot study, and but further extrapolatable to High-Need, High-Risk Veteran patients across several Veteran Integrated Service Networks (VISN) geographically across the country (meaning not encompassing every state, but a geographically wide gamut of several states two-dimensionally). This threat to the validity of the results is not a major threat in this study as the target patient demographic was always intended to be HNHR Veterans, and while some of the work may extrapolate to Veterans not HNHR, or patients with the same demographic qualities receiving care outside the VA health system exclusively, or dually with Medicare and Medicaid services, generalizing the results to beyond

HNHR Veterans receiving care not involving the VA was not part of the scope of the research, though a potential, indirect consequence from it, should it occur.

Insufficient statistical power with Full Model – missingness was not random – MCAR test not reported, but the missingness was addressed by building a parsimonious model, and certain variable missingness and survey interpretability is aligned with high complexity of needs this vulnerable Veteran population usually have.

Missing variable bias for Outcome 1 because the intercept was statistically significant, and variables usually statistically significant for this population were not in the Parsimonious model such as Falls, IADLs, ADLs, markers of mental health. This was addressed in the Outcome 2 models with a non-significant intercept and could have been addressed alongside insufficient statistical power through multiple imputation, but the idea was rejected in favor of leveraging the larger full survey data in the HERO Care survey.

Policy Implications

Recommendations for identifying Veterans with transportation issues include triangulating bulk areas of HNHR Veterans in Rural vs Urban Areas that live too far away from healthcare centers, and that may need home-based primary care services. This may potentially reduce unnecessary acute-care utilization such as emergency room and inpatient hospital stays, and even delay eventual nursing home placement. That, in turn, can be an important next or future step for this research. An example is found in research conducted by Rotenberg et al., The Independence at Home (IaH) Demonstration Year 2 results net projected savings to the Centers for Medicare & Medicaid Services (CMS) after routine billing for IAH services and other advanced alternative payment models was between an interval of $1.8Billion to $10.9Billion based on the quality metrics of rates of emergency department and inpatient admissions for ambulatory care-sensitive conditions[38].

Recommendations to ameliorate the effects depicting being into these latent classes would be to focus on addressing one healthcare need at a time, until after evaluative and programmatic improvement is shown in one domain, moving on towards addressing the next one. While these healthcare and health status domains are multidimensional and inter-correlated, it would seem less of a strain on the VA health system infrastructure, and perhaps more efficient and effective, to address treating one domain of health at a time, and in doing so, perhaps tangentially improving the patient's endorsed health needs on other domains simultaneously. Note: these latent classes are not scale measured, implying that while the domains are inter-related, the latent classes are nominal, and therefore should not be considering as increased levels of health status duress or more healthcare need than others, just perhaps different types of HNHR Veteran patient latent classes they could belong to.

Further novel research could demonstrate if just as HNHR Veteran patients are ranked from lowest to highest risk of mortality and/or hospitalization, so too could a meaningful ranking system be applied to qualitatively define HNHR-Veteran patients that goes beyond the fact that they need the most care, but towards actionable groupings of unmet needs that could be addressed through targeted interventions, ultimately arriving at the same conclusion – get these patients the help they need!

CONCLUSION

The VA CAN score is a statistically significant predictor of acute-care usage as expressed by emergency room and inpatient hospital stays. Transportation-related health barriers to getting primary care are also statistically significantly associated with acute-care usage at varied levels of transportation-less strain, but by-and-large when there is “A lot of trouble” expressed in securing transportation. The latent class analyses helped create four actionable latent classes that could serve as a basis to develop targeted interventions to address the unique unmet needs of these patients. Despite the inherent missingness present in this pilot study, these predictors, and those that remain to be significant due to statistical power issues, lay a foundation for the research on the larger HERO Care survey that lies ahead.

APPENDIX

***Table 0*: Study structure, variables used, and their descriptive statistics**

Binary Outcomes (*Acute-Care Utilization*)							
Variable Name	*Level of Analyses*	*Variable Description*	*Level of Measurement*	*Range*	*Counts*	*Directionality*	*VIF*
Emergency Room Stays	Outcome 1	"In the last 6 months: a) Have you gone to the emergency room for any reason?	Nominal	0 = No, 1 = Yes	No = 195; Yes = 454; Miss = 9	Negative	1.618
Inpatient Hospital Stays	Outcome 2	"In the last 6 months: b) Have you been admitted to the hospital for any reason?	Nominal	0 = No, 1 = Yes	No = 190; Yes = 436; Miss = 32	Negative	1.621
Categorical Factors							
Variable Name	*Variable Type*	*Variable Description*	*Level of Measurement*	*Range*	*Counts*	*Directionality*	*VIF*
Selection Score Groups	Auto generated	Internal VA variable for selecting patients	Ordinal	0 = Less than 0, 1 = 0 to 1, 2 = 2 to 3, 3 = 4 or more	Less than 0 = 192; 0 to 1 = 220; 2 to 3 = 129; 4 or more = 115; Miss = 2		1.803
Fit Clinic (Cate)	Auto generated	If the patient was seen by "Cate" at the Miami Fit Clinic	Nominal	0 = No, 1 = Yes	No = 620; Yes = 14; Miss = 24	Positive	1.178

Fit Clinic	Auto generated	If the patient was seen at the Miami Fit Clinic	Nominal	0 = No, 1 = Yes	No = 502; Yes = 156	Positive	1.46
Fit Clinic (Eddie)	Auto generated	If the patient was seen by "Eddie" at the Miami Fit Clinic	Nominal	0 = No, 1 = Yes	No = 290; Yes = 53; Miss = 315	Positive	1.153
SCI	Auto generated	Has Spinal Cord Injury VA CDW variable	Nominal	0 = No, 1 = Yes	No = 626; Yes = 30; Miss = 2	Negative	1.175
Homebound Status Total Score	Pre-validated	National Health and Aging Trends Study	Ordinal	0 = Not homebound, 1 = Semi homebound, 2 = Homebound	Not homebound = 238; Semi homebound = 129; Homebound = 50; Miss = 241	Negative	1.084
Mailed	Auto generated	Whether the survey was mailed to patient, or administered in-person/phone	Nominal	0 = Survey Mailed, 1 = In-person/phone	Mailed = 467; In-person/phone = 191	Positive	1.785
Balance	Study Specific	"Do you have any current issues with walking, stepping or balance?"	Nominal	0 = No, 1 = Yes	No = 166; Yes = 485; Miss = 7	Negative	1.658

Prosthetics	Study Specific	"Which of these assistive devices do you use the most often?"	Nominal	0 = "I don't use any of these," 1 = "Cane," 2 = "2-wheel walker," 3 = "3-wheel walker," 4 = "4-wheel walker," 5 = "wheel chair"	"I don't use any of these" = 234; "Cane" = 178; "2-wheel walker" = 30; "3-wheel walker" = 10; "4-wheel walker" = 122; "Wheelchair" = 81; Miss = 3	Negative	1.689
Limits Exercise	Study Specific	"Do you have any barriers that limit or prevent you from exercise?"	Nominal	0 = No, 1 = Yes	No = 257; Yes = 386; Miss = 15	Negative	1.406
Pedometer	Study Specific	"Do you own a pedometer, or have you used one before?"	Nominal	0 = No, 1 = Yes	No = 557; Yes = 90; Miss = 11	Positive	1.152
PHQ Screen	Pre-validated	Patient Health Questionnaire-2; 2-item depression inventory screening result	Nominal	0 = Negative, 1 = Positive	Negative = 401; Positive = 209; Miss = 48	Negative	1.513
Has Caregiver	Study Specific	"Do you have a caregiver?"	Nominal	0 = No, 1 = Yes	No = 434; Yes = 224		1.084

Transportation	Study Specific	TP1: "How much trouble is it for you to get transportation to your primary doctors?"	Ordinal	0 = No trouble, 1 = A little trouble, 2 = Some trouble, 3 = A lot of trouble	"No trouble" = 410; "A little trouble" = 93; "Some trouble" = 88; "A lot of trouble" = 60; Miss = 7	Negative	1.841
Scheduling	Study Specific	TP2: "Do you ever delay scheduling a doctor's appointment because transportation is too much trouble?"	Nominal	0 = No, 1 = Yes	No = 500; Yes = 149; Miss = 9	Negative	1.632
Commute	Study Specific	TP3: "How long does it usually take you to get from where you live to your doctor?"	Ordinal	0 = "Less than 30 minutes," 1 = "Between 30 and 59 minutes," 2 = "Between 60 and 120 minutes," 3 = "More than 120 minutes"	"Less than 30 minutes" = 182; "Between 30 and 59 minutes" = 276; "Between 60 and 120 minutes" = 162; "More than 120" = 31; Miss = 7	Negative	1.174

Preferred Contact	Study Specific	Technology Use (TU1): "What is your preferred way to be contacted from the VA? (Please select one)"	Nominal	1 = A (By home phone); 2 = B (By cellphone); 3 = C (By Internet (My Health*e*Vet secure message); 4 = "By mail"	"By home phone" = 152; "By cellphone" = 344; "By internet" = 36; "By mail" = 107; Miss = 19		1.100
Computer Access	Study Specific	TU2: "If you have access to a computer, can you open the Internet and do a search?"	Nominal	0 = No, 1 = Yes	No = 250; Yes = 379; Miss = 29	Positive	1.639
Email	Study Specific	TU3: "Do you use an electronic mail (email)?"	Nominal	0 = No, 1 = Yes	No = 170; Yes = 336; Miss = 152	Positive	1.712
MHV1 Account	Study Specific	TU4: "Are you enrolled in My HealtheVet?"	Nominal	0 = No, 1 = Yes	No = 213; Yes = 292; Miss = 153	Positive	1.419
			Continuous Covariates				
Variable Name	*Level of Analyses*	*Variable Description*	*Level of Measurement*	*Range*	*Mean(se); n*	*Directionality*	*VIF*
ADI State Rank	Auto generated	Area Deprivation Index	Ordinal	1-10	5.36(0.111); 654	Negative	1.25
ADL Total Score	Pre-validated	Barthel Total Score for Activities of Daily Living"	Ordinal	0-100	84.11(0.858); 574	Positive	2.209

CAN Score 1yr	Auto generated	Internal VA prediction resource	Scale	40 - 99	93.25(0.301); 644	Negative	1.4
Falls (Count)	Study Specific	"How many times have you fallen in the past year?"	Ordinal	0 = None, 1 = 1, 2 = 2, 3 = 3, 4 = 4, 5 = 5, 6 = More	1.84(0.077); 648	Negative	1.347
Felt Best	Study Specific	"When was the last time you felt at your best, physically?"	Ordinal	0 = "I felt at my best now," 1 = "I used to feel at my best within the past year," 2 = "I used to feel at my best within the past 3 years," 3 = "I used to feel at my best within the past 5 years," 4 = "It's been more than 5 years than I'm not felt at my best, physically"	2.42(0.053); 639	Negative	1.341
General Health	Study Specific	"In general, how would you rate your health today? (Please select one)"	Ordinal	0 = "Very Good," 1 = "Good," 2 = "Average," 3 = "Bad," 4 = "Very Bad"	1.90(0.036); 654	Positive	1.975

Hierarchical Condition Categories	Auto generated	Total # of HCC conditions CDW variable	Interval	0 - 15	5.45(0.093); 656	Negative	2.114
Medical Forms	Pre-validated	"How confident are you filling medical forms by yourself? (Please select one - Health Literacy)	Ordinal	1 = 1(not confident), 2 = 2, 3 = 3(Somewhat confident), 4 = 4, 5 = 5(Very confident)	3.93(0.051); 649	Positive	1.437
HNHR Group	Author Generated	# of Times Patient was In/Out of HNHR Group from Fiscal Quarters	Ordinal		53.69(1.467); 658	Negative	1.886
IADL Total Score	Primary	Lawton Total Score for Instrumental Activities of Daily Living"	Interval	0-8	6.01(0.087); 593	Positive	2.102
JFI Score	Auto generated	Internal VA frailty measure	Interval	5-11	7.05(0.046); 658		1.562
NOSOS	Auto generated	Internal VA prediction resource	Scale	0.3040-21.3340	3.27(0.123); 655		1.905
Physical Status	Study Specific	"From 1 to 10, with 1 being the worst and 10 being the best, how would you rate	Interval	1 = worst, 10 = best	5.44(0.081); 643	Positive	2.121

		your physical status at this moment? (Please select one)"					
SNI Total Score	Pre-validated	Total Score for Berkman & Syme's Social Network Index	Interval	0-4	5.05(0.092); 556	Positive	1.246
SPA Score	Pre-validated	Self-Perceptions of Aging Total Score	Interval	0-5	3.20(0.061); 616	Positive	
Total VA Resource Use	Author Generated	"Total Resource Use from VA"	Interval	0-17	0.38(0.039); 658	Positive	1.141
Demographic Adjustors							
Variable Name	*Level of Analyses*	*Variable Description*	*Level of Measurement*	*Range*	*Counts/Mean (se); n*	*Directionality*	*VIF*
Race	Auto generated	Race reported by patient	Nominal	0 - White, 1 - Black or African American, 2 - American Indian or Alaska Native, 3 - Native Hawaiian or Other Pacific Islander	"White" = 403; "Black or African American" = 234; "American Indian or Alaska Native" = 1; "Native Hawaiian or Other Pacific Islander" = 5; Miss = 15		1.342

Ethnicity	Auto generated	Ethnicity reported by patient	Nominal	0 = Hispanic or Latino, 1 = Not Hispanic or Latino	"Hispanic or Latino" = 537; "Not Hispanic or Latino" = 113; Miss = 8	1.228
Postal Code (Zip)	Auto generated	Region by city or zip; Limited to Florida	Nominal		Total provided = 341; Miss = 317	1.071
Age	Auto generated	Patients reported age at time of intake	Ratio	39-100	70.61(0.352); 658	1.000

Education	Study Specific	Highest reported educational achievement	Interval	0 = No schooling completed; 1 = Elementary school to 8th grade; 2 = Some high school, no diploma; 3 = Highschool graduate, diploma, or equivalent; 4 Some college credit, no degree; 5 Associate degree; 6 = Bachelor's degree; 7 = Master's degree; 8 = Professional/Doctorate degree	"No Schooling completed" = 2; "Elementary school to 8th grade" = 10; "Some high school, no diploma" = 38; "High school graduate, diploma or equivalent" = 177; "Some college credit, no degree" = 212; "Associate degree" = 65; "Bachelor's degree" = 90; "Master's degree" = 41; "Professional Doctorate degree" = 13; Miss = 10		1.268

***Table 1-1*: Summary statistics and univariate comparisons of associations between both outcomes and categorical predictors (*n* = 658)**

Categorical Factors		*Outcome 1 (Emergency Room Stay)*			*Outcome 2 (Inpatient Hospital Stay)*		
Predictors	*Test type*	*Statistic(df)*	*n(% complete)*	*p-value*	*Statistic(df)*	*n(% complete)*	*p-value*
Selection Score Groups	χ^2	1.506(*3*)	647 (98%)	0.681	1.111(*3*)	624 (95%)	0.775
Fit Clinic (Cate)	LRT	0.476(*1*)	625 (95%)	0.768	1.808(*1*)	603 (92%)	0.218
Fit Clinic	FE	4.663(*1*)	649 (99%)	0.035 **	23.554(*1*)	626 (95%)	< 0.001 ***
Fit Clinic (Eddie)	LRT	0.427(*1*)	338 (51%)	0.625	0.002(*1*)	326 (49%)	1.000
SCI	FE	0.637(*1*)	647 (98%)	0.421	0.388(*1*)	624 (95%)	0.675
Race	LRT	3.685(*3*)	635 (97%)	0.298	6.058(*3*)	611 (93%)	0.109
Ethnicity	FE	0.802(*1*)	641 (97%)	0.364	2.849(*1*)	618 (94%)	0.106
Homebound Status	χ^2	0.669(*2*)	413 (63%)	0.716	0.018(*2*)	400 (61%)	0.991
Mailed	FE	1.238(*1*)	649 (99%)	0.301	1.088(*1*)	626 (95%)	0.295
Postal Code (ZIP)	LRT	137.442(*115*)	336 (51%)	0.068 *	126.908(*110*)	323 (49%)	0.129
Balance	FE	0.001(*1*)	642 (98%)	1.000	2.114(*1*)	620 (94%)	0.158
Has Prosthetics	LRT	7.332(*5*)	646 (98%)	0.147	12.023(*5*)	623 (95%)	0.034 **
Limits on Exercise	FE	2.219(*1*)	634 (96%)	0.155	0.556(*1*)	613 (93%)	0.475
Has Pedometer	FE	0.092(*1*)	638 (97%)	0.803	0.480(*1*)	615 (93%)	0.528
PHQ2 Screening Score	FE	3.402(*1*)	602 (91%)	0.076 *	2.164(*1*)	579 (88%)	0.160
Has Caregiver	FE	0.852(*1*)	649 (99%)	0.367	0.054(*1*)	626 (95%)	0.854

TP1 Transportation	χ^2	14.469(*3*)	643 (98%)	0.002 ***	11.992(*3*)	619 (94%)	0.007 ***
TP2 Scheduling	FE	5.439(*1*)	640 (97%)	0.024 **	3.085(*1*)	617 (94%)	0.097 *
TP3 Commute	χ^2	2.514(*3*)	642 (98%)	0.473	1.655(*3*)	619 (94%)	0.647
TU1 Preferred Contact	χ^2	0.374(*3*)	630 (96%)	0.946	1.244(*3*)	607 (92%)	0.742
TU2 Computer Access	FE	2.894(*1*)	621 (94%)	0.106	2.541(*1*)	599 (91%)	0.124
TU3 Email	FE	3.196(*1*)	500 (76%)	0.081 *	2.200(*1*)	484 (74%)	0.146
TU4 MHV Account	FE	0.025(*1*)	499 (76%)	0.922	0.129(*1*)	483 (73%)	0.764

*Observed significance level breakdown: *, statistically significant below 0.10; **, statistically significant below 0.05; ***, statistically significant below 0.01. Test type: FE, Fisher's Exact test; LRT, Likelihood Ratio test; χ^2, chi-squared test. Test type determination: 2x2 crosstabulation and expected cell count assumption met, Fisher's Exact test; larger than 2x2 crosstabulation and expected cell count assumption met, chi-squared test; Any crosstabulation size and expected cell count assumption unmet, Likelihood Ratio test.*

***Table 1-2*: Summary statistics and univariate comparisons of associations between both outcomes and continuous predictors (*n* = 658)**

Outcome 1 (Emergency Room Stay) ; Outcome 2 (Inpatient Hospital Stay)							
Predictors	Levene's F	*p-value* (F)	*t*(*df*)	*p-value* (*t*)	95% *CI MD*	*ES PE*	95% *CI ES*
ADI State Rank	0.412 ; 0.313	0.521 ; 0.576	-1.554(*620*) ; -1.929(*643*)	0.121 ; 0.054	(-0.868, 0.101) ; (-0.946, 0.008)	-0.136 ; -0.166	(-0.307, 0.036) ; (-0.334, 0.003)
ADL Score	0.841 ; 3.702	0.360 ; 0.055	1.590 (*566*) ; 2.418 (*543*)	0.112 ; 0.016	(-0.699, 6.643) ; (0.865, 8.358)	0.144 ; 0.222	(-0.034, 0.322) ; (0.042, 0.403)
Age	1.570 ; 1.276	0.211 ; 0.259	0.418 (*647*) ; 1.115 (*624*)	0.676 ; 0.310	(-1.195, 1.842) ; (-0.739, 2.320)	0.036 ; 0.088	(-0.132, 0.203) ; (-0.082, 0.258)
CAN Score (1-year)	7.119 ; 3454	0.008 ; 0.420	-4.359 (*240.983*) ; -3.051 (*610*)	<0.001 ; 0.002	(-4.594, -1.736) ; (-3.303, -0.716)	-0.419 ; -0.267	(-0.589, -0.249) ; (-0.438,-0.095)
Education	4.990 ; 3.305	0.026 ; 0.070	1.291 (*325.840*) ; 0.769 (*615*)	0.198 ; 0.442	(-0.090, 0.436) ; (-0.155, 0.354)	0.116 ; 0.068	(-0.054, 0.286) ; (-0.105, 0.240)
Falls	6.532 ; 0.646	0.422	-3.587 (*412.415*) ; -1.972 (*615*)	<0.001 ; 0.049	(-0.875, -0.256) ; (-0.670, -0.001)	-0.293 ; -0.172	(-0.462, -0.123) ; (-0.343, -0.001)
Felt Best	1.206 ; 5.420	0.273 ; 0.020	0.688 (*628*) ; -0.778 (*326.765*)	0.491 ; 0.437	(-0.149, 0.309) ; (-0.332, 0.144)	0.060 ; -0.071	(-0.111, 0.231) ; (-0.243, 0.101)
General Health	1.414 ; 0.474	0.235 ; 0.491	3.282(*643*) ; 2.923(*620*)	< 0.001 ; 0.004	(0.104, 0.412) ; (0.077, 0.394)	0.281 ; 0.255	(0.113, 0.450) ; (0.083, 0.427)
HCC	0.004 ; 0.604	0.951 ; 0.437	-2.273 (*645*) ; -1.667 (*622*)	0.023 ; 0.096	(-0.859, -0.063) ; (-0.753, 0.062)	-0.195 ; -0.145	(-0.363, -0.026) ; (-0.316, 0.026)

Health Literacy	3.483 ; 1.705	0.062 ; 0.192	0.621 (*640*) ; 0.318 (*616*)	0.267 ; 0.375	(-0.150, 0.289) ; (-0.188, 0.261)	0.054 ; 1.306	(-0.115, 0.222) ; (-0.144, 0.199)
HNHR Group	2.000 ; 0.173	0.158 ; 0.678	-2.347 (*645*) ; -2.786 (*622*)	0.019 ; 0.005	(-0.679, -0.060) ; (-0.753, -0.130)	-0.201 ; -0.242	(-0.369, -0.033) ; (-0.413, -0.071)
IADL Score	0.729 ; 1.451	0.394 ; 0.229	1.593 (*584*) ; 1.870 (*562*)	0.112 ; 0.062	(-0.071, 0.682) ; (-0.007, 0.731)	0.144 ; 0.171	(-0.033, 0.322) ; (-0.009, 0.350)
JFI Score	0.654 ; 0.751	0.419 ; 0.386	-0.045 (*647*) ; -0.068 (*624*)	0.924 ; 0.946	(-0.204, 0.189) ; (-0.210, 0.196)	-0.008 ; -0.006	(-0.176, 0.159) ; (-.176, 0.164)
NOSOS Score	0.633 ; 0.651	0.427 ; 0.386	0.721 (*644*) ; 0.903 (*621*)	0.471 ; 0.367	(-0.339, 0.732) ; (-0.295, 0.797)	0.062 ; 0.078	(-0.106, 0.230) ; (-0.092, 0.249)
Physical Status	0.716 ; 0.670	0.398 ; 0.413	1.958 (*632*) ; 1.912 (*610*)	0.051 ; 0.056	(-0.001, 0.696) ; (-0.009, 0.697)	0.170 ; 0.167	(-0.001, 0.340) ; (-0.004, 0.339)
SNI Score	0.001 ; 2.444	0.979 ; 0.119	1.364 (*548*) ; 0.934 (*531*)	0.173 ; 0.351	(-0.120, 0.663) ; (-0.206, 0.580)	0.126 ; 0.087	(-0.055, 0.306) ; (-0.385, -0.034)
SPA Score	2.817 ; 2.506	0.094 ; 0.114	-1.117 (*607*) ; -2.348 (*585*)	0.264 ; 0.019	(-0.413, 0.113) ; (-0.590, -0.053)	-0.098 ; -0.210	(-0.271, 0.074) ; (-3.85, -0.034)
Total VA-Resource Use	0.173 ; 2.029	0.678 ; 0.155	0.016 (*647*) ; -1.004 (*624*)	0.987 ; 0.316	(-0.167, 0.169) ; (-0.261, 0.084)	0.001 ; -0.087	(-0.166, 0.169) ; (-0.257, 0.083)

CI, confidence interval; MD, mean difference; ES, effect size (Hedge's Correction/G); PE, point estimator.

*Observed significance level breakdown: *, statistically significant below 0.10; **, statistically significant below 0.05; ***, statistically significant below 0.01.*

***Table 2*: Logistic regression model testing multivariate associations for both outcomes with model fit estimates, and mixture of categorical and continuous predictors, using generalized linear modeling**

*Full Model**	*ERS*: No=121(32%), Yes=262(68%), n=383*					*IHS*: No=118(32%), Yes=251(68%), n=369*				
*Predictor**		*Wald*	*p-value*	*OR*	*95% CI OR*		*Wald*	*p-value*	*OR*	*95% CI OR*
Intercept		6.182	0.013	0.01	(0.000, 0.374)		0.054	0.816	0.676	(0.025, 18.287)
*Categorical Predictors**										
*Predictor**	*n(%)*	*Wald*	*p-value*	*OR*	*95% CI OR*	*n(%)*	*Wald*	*p-value*	*OR*	*95% CI OR*
Email*										
No (ref) = 0	117(31%)					113(31%)				
Yes = 1	266(70%)	0.345	0.557	0.848	(0.490, 1.469)	256(69%)	0.389	0.533	0.839	(0.483, 1.457)
Fit Clinic*										
Unseen (ref) = 0	282(74%)					271(73%)				
Seen = 1	101(26%)	1.452	0.228	0.722	(0.426, 1.226)	98(27%)	10.189	0.001	0.425	(0.251, 0.719)
PHQ2 Screen*										
Negative (ref) = 0	260(68%)					252(68%)				
Positive = 1	123(32%)	0.257	0.612	0.858	(0.644, 2.109)	117(32%)	1.777	0.183	0.664	(0.363, 1.213)
Prosthetics*										
Don't use any (ref) = 0	148(39%)					141(38%)				

Cane = 1	111(29%)	4.068	0.044	0.532	(0.288, 0.982)	108(29%)	2.212	0.137	0.628	(0.340, 1.160)
2-wheel walker = 2	14(4%)	0.019	0.891	1.109	(0.252, 4.888)	13(4%)	0.243	0.622	1.526	(0.285, 8.181)
3-wheel walker = 3	6(2%)	0.074	0.786	1.378	(0.136, 13.934)	6(2%)	0.003	0.955	0.937	(0.096, 9.115)
4-wheel walker = 4	72(19%)	1.083	0.298	0.671	(0.317, 1.422)	69(19%)	1.691	0.193	0.606	(0.285, 1.289)
Wheel chair = 5	32(8%)	0.028	0.867	0.905	(0.280, 2.928)	32(9%)	4.591	0.032	0.287	(0.092, 0.899)
Scheduling*										
No (ref) = 0	299(78%)					286(78%)				
Yes = 1	84(22%)	0.154	0.695	1.166	(0.542, 2.505)	83(23%)	0.494	0.482	1.320	(0.608, 2.866)
Transportation*										
No Trouble (ref) = 0	247(65%)					237(64%)				
A Little Trouble = 1	56(15%)	0	0.998	1.001	(0.488, 2.051)	54(15%)	0.067	0.795	1.104	(0.525, 2.321)
Some Trouble = 2	52(14%)	1.115	0.291	1.611	(0.665, 3.901)	51(14%)	0.199	0.656	0.825	(0.355, 1.918)
A Lot of Trouble = 3	28(7%)	3.244	0.072	3.666	(0.892, 15.070)	27(7%)	3.518	0.061	4.724	(0.933, 23.931)
*Continuous Predictors**										
Predictor (Min;Max)*	*Mean(SD)*	*Wald*	*p-value*	*OR*	*95% CI OR*	*Mean(SD)*	*Wald*	*p-value*	*OR*	*95% CI OR*
ADL Score (5;100)	86.63(18.841)	0.014	0.907	1.001	(0.981, 1.022)	86.56(19.038)	0.426	0.514	0.993	(0.973, 1.014)

CAN Score (1yr) (40;99)	92.52(8.245)	13.737	<0.001	1.066	(1.030, 1.102)	92.46(8.284)	3.072	0.080	1.027	(0.997, 1.059)
Falls (Count) (0;6)	1.80(1.946)	6.222	0.013	1.202	(1.040, 1.389)	1.83(1.952)	1.875	0.171	1.103	(0.959, 1.269)
General Health (0;4)	1.96(0.907)	5.602	0.018	0.635	(0.436, 0.925)	1.98(0.916)	1.102	0.315	0.826	(0.569, 1.199)
HCC (1;14)	5.30(2.326)	0.213	0.645	0.973	(0.865, 1.094)	5.27(2.320)	0.021	0.886	1.009	(0.895, 1.137)
HNHR Group (Count) (1;9)	3.83(1.862)	0.008	0.930	0.994	(0.866, 1.140)	3.83(1.826)	1.604	0.205	1.096	(0.951, 1.264)
IADL Score (0;8)	6.24(1.920)	0.339	0.561	1.052	(0.888, 1.246)	6.24(1.929)	0.067	0.796	0.977	(0.818, 1.166)
Physical Status (1;10)	5.47(1.975)	0.663	0.416	1.076	(0.902, 1.284)	5.47(1.995)	0.352	0.553	0.949	(0.797, 1.129)
SPA Score (0;5)	3.15(1.553)	0.958	0.328	0.909	(0.752, 1.100)	3.15(1.560)	0.250	0.617	0.953	(0.790, 1.150)

**Notes: Binary logistic regression; Full Model, Model 1, complete case analysis for each outcome, unadjusted; Outcome 1 (ERS), emergency room stay; Outcome 2 (IHS), inpatient hospital stays. *Predictor: n(%), sample size with percent complete; Wald, Wald chi-square test-statistic; OR, odds ratio; 95% CI OR, 95% confidence interval of the odds ratio; Min, minimum; Max, maximum; Mean, summated average; SD, standard deviation. *Categorical Predictors: Email, "Do you use an electronic mail (email)?", Fit Clinic, seen in Fit Clinic; PHQ2 score, PHQ2 screening result; Prosthetics, "Which of these assistive devices do you use the most often?", Scheduling, "Do you ever delay scheduling a doctor's appointment because transportation is too much trouble?"; Transportation, "How much trouble is it for you to get transportation to your primary doctors?". *Continuous Predictors: ADL Score, Barthel's Activities of Daily Living scale, total score; CAN Score (1yr), Care Assessment Needs 1 year estimated probability of death or hospitalization within the past year, expressed as a percentile from 0 (lowest risk) to 99 (highest risk), generated from Veterans Affairs (VA) Corporate Data Warehouse (CDW) administratively after survey was administered and data collected;* Falls *(Count), "How many times have you fallen in the past year?" (0 - None, 6 - More than 5); General Health, "In general, how would you rate your health today?" (0 - Very Bad, 4 - Very Good); HCC, administratively generated from VA CDW after data collected, total chronic healthcare conditions a patient has as listed by CDW (1 - 1 chronic condition, 14 - 14 chronic conditions); HNHR Group (Count), number of fiscal quarters Veteran patient was considered a High-Need, High-Risk (HNHR) patient within the study time horizon (2 years) (1 - 1 quarter, 9 - 9 quarters), variable does not account for entering, leaving, and then returning to status,* *only total frequency of quarters identified as HNHR; IADL Score, IADL Score, Lawton's Instrumental Activities of Daily Living* (*0 - low functioning, 8 – high functioning*)*; Physical Status, "From 1 to 10, with 1 being the worst and 10 being the best, how would you rate your physical status at this moment?* (*Please select one*)*"; SPA Score, using Attitudes Toward Own Aging subscale measuring Self-Perception of Aging,* (*0 - more negative self-perception of aging, 5 - more positive self-perception of aging*).

***Table 3-1*: Model fit estimates from both full and parsimonious binary logistic regression models**

Outcome 1			*Outcome 2*		
Model 1 Full GLM Binary Logistic Regression Model Fit Estimates by Outcome					
AIC	*BIC*	*-2LL*	*AIC*	*BIC*	*-2LL*
473.32	560.18	-214.66	462.94	548.98	-209.47
Hosmer and Lemeshow Test					
	chi^2 (df)	*p-value*		*chi^2 (df)*	*p-value*
Step 1	1.97 (*1*)	0.98	Step 1	3.76 (*8*)	0.88
Omnibus Tests of Model Coefficients					
	chi^2 (df)	*p-value*		*chi^2 (df)*	*p-value*
Step 1	48.48 (*21*)	< 0.001	Step 1	43.57 (*21*)	0.003
Model 1	48.48 (*21*)	< 0.001	Model 1	43.57 (*21*)	0.003
Model 2 Parsimonious GLM Binary Logistic Regression Model Fit Estimates by Outcome					
AIC	BIC	-2LL	AIC	BIC	-2LL
299.97	326.65	-143.99	365.27	396.11	-175.633
Hosmer and Lemeshow Test					
	chi^2 (df)	*p-value*		*chi^2 (df)*	*p-value*
Step 13	8.47 (*1*)	0.39	Step 12	10.96 (*8*)	0.20
Omnibus Tests of Model Coefficients					
	chi^2	*p-value*		*chi^2*	*p-value*
Step 13	-2.37 (*1*)	0.124	Step 12	-1.86 (*1*)	0.172

Model 13	33.47 (*5*)	< 0.001	Model 12	30.51 (*6*)	< 0.001

**Model fit: AIC, Akaike Information Criteria; BIC, Bayesian Information Criteria; -2LL, log-likelihood; chi^2(df), chi-square test statistic with degrees of freedom; Hosmer and Lemeshow Test non-significant value, good logistic regression model fit; Omnibus Tests of Model logistic regression model fit; Omnibus Tests of Model Coefficient, step significance means extra stepwise procedure was significant compared to previous step, model significance.*
Means overall model was significant. Model number, final step for stepwise procedure.

Table 4: **Univariate missingness of both outcomes across covariates and factors**

Emergency Room Stay	*Present*						*Missing*		
	Count			*Percent*			*Percent*		
Variables	*Total*	*Yes*	*No*	*Total*	*Yes*	*No*	*Total*	*Yes*	*No*
Email	506	347	153	76.9%	76.4%	78.5%	23.1%	23.6%	21.5%
ADL Score	574	393	175	87.2%	86.6%	89.7%	12.8%	13.4%	10.3%
IADL Score	593	413	173	90.1%	91.0%	88.7%	9.9%	9.0%	11.3%
PHQ2 Screen	610	420	182	92.7%	92.5%	93.3%	7.3%	7.5%	6.7%
Outcome 2 (IHS)	626	428	191	95.1%	94.3%	97.9%	4.9%	5.7%	2.1%
Physical Status	643	446	188	97.7%	98.2%	96.4%	2.3%	1.8%	3.6%
SPA Score	616	424	185	97.7%	98.2%	96.4%	2.3%	1.8%	3.6%
CAN Score (1yr)	644	442	193	97.9%	97.4%	99.0%	2.1%	2.6%	1.0%
Falls (Count)	648	447	192	98.5%	98.5%	98.5%	1.5%	1.5%	1.5%
Scheduling	649	448	192	98.6%	98.7%	98.5%	1.4%	1.3%	1.5%
Transportation	651	450	193	98.9%	99.1%	99.0%	1.1%	0.9%	1.0%
General Health	654	451	194	99.4%	99.3%	99.5%	0.6%	0.7%	0.5%
Prosthetics	655	452	194	99.5%	99.6%	99.5%	0.5%	0.4%	0.5%
HNHR Group (Count)	656	452	195	99.7%	99.6%	100.0%	0.3%	0.0%	0.4%
HCC	656	452	195	99.7%	99.6%	100.0%	0.3%	0.4%	0.0%

Inpatient Hospital Stay	*Present*						*Missing*		
	Count			*Percent*			*Percent*		
Variables	*Total*	*Yes*	*No*	*Total*	*Yes*	*No*	*Total*	*Yes*	*No*
Email	506	337	147	76.9%	77.3%	77.4%	23.1%	22.7%	22.6%
ADL Score	574	372	173	87.2%	85.3%	91.1%	12.8%	14.7%	8.9%
IADL Score	593	392	172	90.1%	89.9%	90.5%	9.9%	10.1%	9.5%
PHQ2 Screen	610	396	183	92.7%	90.8%	96.3%	7.3%	9.2%	3.7%
SPA Score	616	407	180	93.6%	93.4%	94.7%	6.4%	6.7%	5.3%
Physical Status	643	424	188	97.7%	97.3%	99.0%	2.3%	2.8%	1.1%
CAN Score (1yr)	644	423	189	97.9%	97.02%	99.5%	2.1%	3.0%	0.5%

Falls (Count)	648	427	190	98.5%	97.9%	100.0%	1.5%	2.1%	0.0%
Outcome 1 (ERS)	649	432	187	98.6%	99.1%	98.4%	1.4%	0.9%	1.6%
Scheduling	649	432	185	98.6%	99.1%	97.4%	1.4%	0.9%	2.6%
Transportation	651	434	185	98.9%	99.5%	97.4%	1.1%	0.5%	2.6%
General Health	654	435	187	99.4%	99.8%	98.4%	0.6%	0.2%	1.6%
Prosthetics	655	436	187	99.5%	100%	98.4%	0.5%	0.0%	1.6%
HNHR Group (Count)	656	435	189	99.7%	99.8%	99.5%	0.3%	0.2%	0.5%
HCC	656	435	189	99.7%	99.8%	99.5%	0.3%	0.2%	0.5%

**Notes: Total N = 658 (both outcomes; total N (Outcome 1) = 649; total N (Outcome 2) = 626; n(Yes - Outcome 1) = 454; n(Yes - Outcome 2) = 436; n(No - Outcome 1) = 195; n(No - Outcome 2) = 190; n(Missing - Outcome 1) = 9; n(Missing - Outcome 2) = 32).*

***Table 5*: Parsimonious model using backward stepwise (likelihood ratio) elimination binary logistic regression, empirical variable selection strategy, with generalized linear modeling approach**

**Parsimonious Model*	*ERS [n=630(95.7%); No=191(30.3%); Yes=439(69.7%)]*					*IHS [n=606(92.1%); No=184(30.4%); Yes=422(69.6%)]*				
*Predictor**	*M(SD); n(%)*	*Wald(df)*	*p-value*	*OR*	*95% CI OR*	*M(SD); n(%)*	*Wald(df)*	*p-value*	*OR*	*95% CI OR*
Intercept	X	10.978(1)	<0.001	0.023	(0.002,0.214)	X	2.456(1)	0.117	0.168	(0.018, 1.562)
CAN Score (1yr) (40-99)	93.23 (7.683)	19.819(1)	<0.001	1.054	(1.030, 1.079)	93.25 (7.588)	7.639(1)	0.006	1.033	(1.010, 1.058)
General Health (0-4)	1.90 (0.909)	4.235(1)	0.04	0.806	(0.656, 0.990)	1.91 (0.916)	2.198(1)	0.138	0.849	(0.684, 1.054)
Transportation	630 (100%)		X			606 (100%)		X		
No Trouble (ref) = 0	398 (63.2%)					382 (63.0%)				
A Little Trouble = 1	90 (14.3%)	0.023(1)	0.881	0.963	(0.586, 1.582)	87 (14.4%)	0.022(1)	0.883	1.040	(0.620, 1.745)
Some Trouble = 2	85 (13.5%)	2.845(1)	0.092	1.666	(0.921, 3.015)	84 (13.9%)	0.574(1)	0.449	1.250	(0.702, 2.228)
A Lot of Trouble = 3	57 (9.0%)	6.101(1)	0.014	2.980	(1.253, 7.089)	53 (8.7%)	6.740(1)	0.009	3.330	(1.343, 8.256)
Fit Clinic						606 (100%)		X		
Unseen (ref) = 0			X			460 (75.9%)				
Seen = 1						146 (24.1%)	16.866(1)	<0.001	0.435	(0.293, 0.647)

**Notes: Parsimonious Model, Model 2, complete case analysis for each outcome after backward stepwise elimination,* *unadjusted; Outcome 1 (ERS), emergency room stay; Outcome 2 (IHS), inpatient hospital stays.*

**Predictor: M(SD), summated average and standard deviation; n(%), sample size with percent complete; Wald, Wald Chi-square test-statistic; OR, odds ratio; 95% CI OR, 95% confidence interval of the odds ratio.*

**Categorical Predictors: Transportation, "How much trouble is it for you to get transportation to your primary doctors?"; Fit Clinic, Seen at the Fit Clinic at the VA, administratively generated during data collection phase as intention-to-treat Veterans as part of routine care at the Miami Veterans Affairs Medical Center (VAMC).*

**Continuous Predictors: CAN Score (1yr), Care Assessment Needs 1 year estimated probability of death or hospitalization within the past year, expressed past year, expressed as a percentile from 0 (lowest risk) to 99 (highest risk), generated from Veterans Affairs (VA) Corporate Data Warehouse (CDW) administratively after survey was administered and data collected; General Health, "In general, how would you rate your health today?" (0 - Very Bad, 4 - Very Good).*

X, was not measured for that model, either removed during stepwise elimination, or not provided or relevant.

***Table 6*: Latent class analysis of study participants to determine patient-centered class structure (*n*=617)**

Latent Class Model	AIC	BIC	ABIC	*p* for LMR	Class Comparison	*p* for Bootstrap
2-class	31171.25	31609.32	31295.01	<0.0000	2 vs 1	<0.0000
3-class	30167.35	30826.66	30353.61	<0.0000	3 vs 2	<0.0000
4-class	*29778.99*	*30659.54*	*30027.75*	*0.0098*	*4 vs 3*	*<0.0000*
5-class	29575.23	30677.02	29886.49	0.6268	5 vs 4	<0.0000

Final class counts & proportions based on likely latent class membership

Latent Class Names	*Counts*	*%*	*Latent Class Descriptions*
HNHR-A	69	11%	Has Caregiver and Married, Major Physical Function issues, Major Frailty & Dependence, is Receiving care at home, Has Fallen, Major poor self-perceptions of aging, Major social network deficits, Major technology use deficits; *Uniquely characterized by having caregiver and not being unmarried, the highest in need of healthcare, attention, and socialization*
HNHR-B	188	30%	No Caregiver and Unmarried, Minor Mobility Difficulties and Uses Assistive Devices, Moderate poor self-perception of aging, Moderate poor physical status rating, has fallen; Still Ambulatory but Needs Assistive Devices, despite fall, *uniquely characterized as the threshold of no socialization outside home, not yet bed-ridden*
HNHR-C	224	36%	No Caregiver and Unmarried, Has Fallen, Minor poor self-perception of aging, Minor physical status rating; Still Ambulatory and Social, *uniquely characterized by having Fallen*
HNHR-D	136	22%	Depressed, No Caregiver and Unmarried, Poor Physical Self-Rating and Movement, Still Ambulatory and Social, Not Fallen, *uniquely characterized by mental health deficits (depression)*

Patient-centered latent class endorsement by survey items, descriptions, and classes; estimates in probability scale

Items	*Item Description*	*Latent Class 1*	*Latent Class 2*	*Latent Class 3*	*Latent Class 4*
FS1	Feeling Tired	*0.723*	0.504	0.389	0.069
FS2	Difficulty walking up steps	*0.954*	*0.901*	0.652	0.106

FS3	Difficulty walking without aids	*0.968*	*0.899*	0.678	0.056
FS4	<5% weight decrease	0.331	0.329	0.389	0.239
DCG1	Have a Caregiver	0.182	0.512	*0.843*	*0.870*
SNI1	Currently Married	0.389	0.530	*0.606*	*0.592*
SNI2	Telephone w/ others	*0.625*	0.513	0.455	0.309
SNI3	Get together w/ others	*0.828*	*0.787*	0.719	0.571
SNI4	Attend religious services	*0.917*	0.641	0.585	0.615
SNI5	Attend meetings/clubs	*0.903*	0.742	0.633	0.562
TP1	Transportation issue to primary doctors	0.381	0.321	0.201	0.041
TP2	Scheduling issues b/c transportation	*0.397*	0.326	0.206	0.065
TP3	Distance to primary doctor	*0.364*	*0.331*	0.285	0.250
PF1	General health rating	*0.598*	0.491	0.273	0.031
PF2	Issues walking/balance	*0.941*	*0.967*	0.826	0.209
PF3	Use assistive device	0.190	0.911	0.623	0.144

PF4	Have fallen	*0.817*	*0.834*	0.618	0.319
PF5	Physical Status rating	0.129	0.176	0.223	*0.782*
PF6	Felt best physically	*0.557*	*0.554*	*0.505*	0.200
PF7	Has exercise barriers	*0.839*	*0.759*	0.619	0.196
PF8	Have/used pedometer	*0.982*	0.886	0.825	0.817
PF10	Free pedometer interest	*0.513*	0.294	0.352	*0.493*
ADL1	ADL Feeding	*0.733*	0.130	0.019	0.000
ADL2	ADL Bathing	*0.787*	0.227	0.028	0.027
ADL3	ADL Grooming	*0.764*	0.143	0.009	0.015
ADL4	ADL Dressing	*0.938*	0.425	0.039	0.041
ADL5	ADL Bowels	*0.733*	0.382	0.180	0.070
ADL6	ADL Bladder	*0.823*	0.502	0.298	0.132
ADL7	ADL Toilet Use	*0.832*	0.305	0.077	0.052
ADL8	ADL Transfers	*0.824*	0.174	0.018	0.000

ADL9	ADL Mobility	*0.823*	0.309	0.029	0.013
ADL10	ADL Stairs	*0.965*	*0.734*	0.214	0.008
IADL1	IADL Telephone	0.166	0.000	0.017	0.053
IADL2	IADL Shopping	*1.000*	*0.872*	0.261	0.110
IADL3	IADL Food preparation	*1.000*	*0.842*	0.249	0.163
IADL4	IADL Housekeeping	*0.710*	0.231	0.043	0.045
IADL5	IADL Laundry	*0.969*	0.519	0.096	0.106
IADL6	IADL Mode Transportation	*0.815*	0.274	0.026	0.015
IADL7	IADL Medication Adherence	*0.908*	0.353	0.022	0.024
IADL8	IADL Handle Finances	*0.574*	0.071	0.000	0.015
TU1	Preferred Contact Method	*0.571*	*0.461*	0.315	0.353
TU2	Open Internet and Search	*0.681*	0.432	0.348	0.279
TU4	Use email	*0.498*	*0.491*	0.385	0.352
PHQ	Depression Screen	0.380	0.539	0.670	*0.957*

SPA1	Worse as older	*0.822*	*0.822*	*0.818*	0.459
SPA2	Pep same as last year	*0.784*	*0.757*	0.682	0.410
SPA3	Useless feeling older	*0.773*	0.600	0.548	0.110
SPA4	Happy now as before	*0.796*	*0.799*	*0.737*	0.420
SPA5	Things better older	*0.811*	*0.791*	*0.713*	0.324

Notes: p, p-value; AIC, Akaike Information Criteria; BIC, Bayesian Information Criteria; aBIC, Sample size adjusted Bayesian Information Criteria; LMR, Lo-Mendel-Rubin Adjusted Likelihood Ratio Test; Bootstrap, Parametric Bootstrapped Likelihood Ratio Test; Bootstrap, Parametric Bootstrapped Likelihood Ratio Test for H0 versus Ha Classes; Items chosen as part of latent class by p > 0.500.

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CHAPTER 3

THE HERO CARE SURVEY VALIDATION INITIATIVE: QUANTIFYING THE UNMET NEEDS OF UNITED STATES VETERANS

ABSTRACT

The Home Excellence Resource Center to Advance, Redefine, and Evaluate Non-Institutional Care (HERO Care) survey is a longitudinal multi-site, multi-stakeholder primary data collection initiative. It involves five Department of Veteran Affairs (VA) Medical Centers (VAMC), the Geriatrics Extended Care Data Analysis Center (GECDAC), the Elizabeth Dole Center of Excellence in Veteran and Caregiver Research (EDCoE), the RAND Corporation, and other, with the aim of identify and measure the unmet needs of Veterans and their caregivers. However, there is a need to psychometrically validate this survey. The purpose of this study was to assess the psychometric properties of the HERO Care survey. We do this to decipher which health factors it measures are associated with acute-care utilization [emergency room stays (ERS) and inpatient hospital stays (IHS)], and unmet healthcare and unmet mental health needs. Using a cross-section of the first timewave of data of the Veteran survey – 8,056 Veterans across 4 sites – factor analyses were used to: explore the dimensionality of the survey; identify which model structure fit the survey data well; and assess its psychometric validity, including associations with study outcomes. We found that a 17-factor structure model fit the data adequately, and over 50% of factors were associated with the study outcomes. Our recommendation is to inform policy that supplies healthcare resources to address the triggering health factors we found to meet the Veterans unmet needs and prevent or delay their acute-care utilization.

Word count: 234

Key phrases: HERO Care; psychometric validation; acute-care utilization; Veterans; caregivers

INTRODUCTION

Previous studies have shown an inter-related web of indicators and domains of health that converge to assess a patient’s overall health and well-being. Within the recent years of the pandemic and its ongoing effects on humanity, many of these indicators revolve around the following domains:

> Transportation to healthcare; homebound status; mobility and function; mental health, resiliency, and substance abuse; indicators measuring social networks and support; insecurity of resources such as food, financial recourses, and medication;

perceptions of physical health status; frailty and physical disabilities; perceptions about quality of life and pain; technological use; and the impact of the Covid-19 pandemic on patient health.

Health factors are of related importance to the longevity of patient's days in their communities with their loved ones, on having a prolific quality of life, and the sustenance of healthcare resources towards the refinement of health services. Integrated health systems are deeply affected by acute-care utilization, which plays a pivotal and heavy role on health system financial infrastructures, and the personal, social, and communal burdens on patients and their caregivers. This burden, along with treating these patients, is complex, and requires multi-disciplinary action.

Ongoing work from a multi-site, multi-stakeholder initiative by five Department of Veteran Affairs (VA) Medical Centers (VAMC), the Elizabeth Dole Center for Excellence in Veteran and Caregiver Research (EDCoE), The RAND Corporation, and others, has culminated in the creation of the Home Excellence Resource Center to Advance, Redefine, and Evaluate Non-Institutional Care (HERO Care) survey. Beginning as a pilot study (the HNHR-658) in 2017, it was developed through the COVID-19 pandemic and launched longitudinally across a three-year time-horizon. Based on the RAND *Hidden Heroes* research report (RAND 2014) and the EDCoE initiative to expand VA resources to aide Veteran-caregivers, this survey is intended to acquire primary data not collected in the VA Corporate Data Warehouse (CDW) and measure the unmet needs of Veteran patients and their caregivers. However, there is a need for the survey to be psychometrically valid and reliable, so it could be used to make evidence-based associations on important VA health system outcomes and patient unmet needs.

Unmet needs can be characterized as being two-folded: the first dimension is the type of unmet need that need not be exclusively healthcare related but could also incorporate a patient's quality of life and well-being. The second dimension is that if that need remains unfulfilled for too long, it begins by affecting the patient's health and well-being, but its deleterious effects soon cascade towards affecting their families and loved ones, their communities, and ultimately their societies and health systems. To address unmet needs, it is imperative to explore and understand the gamut of types of unmet needs, understand what the patients' unmet needs are, and address them in a both adequate and timely fashion. This study is a population health-based psychometric survey validation using a health systems approach because it is an effective, low-cost way of trying to understand as much about unmet needs as quickly and widespread as we can, given the proverbial finitude of healthcare resources.

The purpose of this study was to psychometrically validate the HERO Care survey and decipher which of the factors of health it measures are statistically significantly associated with acute-care utilization [emergency room stays (ERS), and inpatient hospital stays (IHS)]. We also intended on validating the HERO Care survey to see what factors are associated with patient unmet healthcare and unmet mental health needs. There is a large, concentrated sense of trust for research and development in healthcare, which very frequently informs the policies we make and vote for, that channel resources towards addressing important, common goals. Without a properly functioning tool, administrators, politicians, and advocates cannot confidently rely on the results of this survey, and therefore we cannot make the associations needed to achieve the health system and patient health outcomes we intend to address.

METHODS

Instrument

There were nearly 200 unique questions in the HERO Care survey, and it spanned 16 pages when printed front and back. 102 survey items were used to perform the factor analyses needed to psychometrically validate this survey, and generally consisted of questions that were anchored by Likert scales that ranged between two to ten response categories or were continuous. These items were chosen because they measured various aspects of health, either as predictors or outcomes.

The remaining questions that were not part of the analyses fell under two types of questions. The first type of questions asked about caregiving, such as whether the Veteran is a caregiver, how was the dynamic of caregiving they were receiving, the logistics of who was giving the care and how it was receiving. The second type of questions were not anchored on ordinal Likert scales, therefore, not of much use for factor analytic methods.

Outcomes

There were two types of outcomes for this study: eight acute-care utilization variables that were drawn from the VA data repository at the patient level, and two different unmet needs questions that were dichotomously measured within the survey. Acute-care utilization was measured as either half emergency room stays (ERS), and the other half as inpatient hospital stays (IHS). Within each half of the acute-care usage outcome types, there were several subtypes: baseline variables which were the counts of ERS/IHS in the year prior to the survey index date, follow up variables that were the count of ERS/IHS in the year after the survey index date; total ERS/IHS as the two-year count of acute-care by the patient within the combined pre- and post-year index date (so a combination of the previous two); and Any ERS/IHS, being the binary measure of 0 = No ERS/IHS versus 1 = at least one count (or any) ERS/IHS.

The other two outcomes were also dichotomously measured and were about the unmet needs of Veteran patients. The first unmet need survey question asked if within the past 12 months if the patient needed healthcare but did not receive it. The second unmet need survey question asked if the patient needed help for their emotions, mental health, or substance use, but did not receive it.

Predictors

Using SPSS version 29, item-level descriptive statistics were calculated, measuring the counts and percents of each survey item's responses (ranging from 2-10 categories, based off the question). The survey item's types were a mixture of study-specific, pre-validated, or "database data," drawn administratively from the VA data repository post survey index date. The study-specific items were generated for the original purpose of this project, intended to measure constructs related to those of interest to stakeholders, and to be validated within this context. Pre-validated, items taken from questionnaires that were previously validated psychometrically.

Database data items were downloaded from medical records within the Veteran Affairs (VA) Corporate Data Warehouse (CDW) rather than determined via survey response. These items were populated with an index date in the VA's database whenever a Veteran checks into any Veterans Affairs Medical Center (VAMC) across the country. Certain other measures are also auto-generated quarterly to help administrators identify which Veterans are at the highest tier of need for services and clinical complexity – hence the term "auto-generated" for these data. See Table 0 in the Appendix for the item-level descriptive statistics.

Data collection

The HERO Care survey is a novel attempt, funded by the Elizabeth Dole Center for Excellence in Veteran and Caregiver Research, the Department of Veteran Affairs, and consists of a multi-sector initiative and collaboration across several Veteran Affairs Medical Centers (VAMC) and Veteran Integrated Service Network-8 (VISN-8), among other stakeholders. It was originally sent out to 20,000 Veterans and their Caregivers as an initiative to collect data that was not currently present in the Department of Veteran Affairs (VA) Corporate Data Warehouse (CDW), across three timewaves of data collection, spanning a total time-horizon of three years of data collection plus the two years of survey design and strategic survey distribution and planning prior to the data collection. Between each data collection phase, the survey was re-evaluated, and many expert round-table discussions were had weekly to gauge which items to remove or add. This acquisition of sustained effort was possible due to stakeholder support throughout. The survey design, layout, and overall intellectual paradigm is modeled after its predecessor pilot study, the "High-Need, High-Risk"-658 (HNHR-658) borrowing items, domains, and lessons learned from that pilot and implemented here in the HERO Care survey.

Factor Analysis – Assessing Psychometric Properties

To assess the psychometric properties of the HERO Care survey, exploratory factor analyses (EFA) was used to assess the dimensionality of the survey, where confirmatory factor analysis (CFA) were used to confirm if the proposed factor model derived from the results of the EFA fit the data well. The CFA also assessed the construct validity of the survey and helped create subscales within the HERO Care survey by calculating summated averages of the items found to measure similar latent constructs. To assess the convergent validity of the HERO Care survey, several types of regression methods were used to associate the factors generated from the CFA results to various acute-care usage variables auto-generated from the VA CDW. The factor analyses were performed using MPLUS version 8.5, where the EFA used Geomin rotation – oblique type, and the CFA used the unweighted least-squares mean-variance estimation method.

Convergent Validity Testing – Regression of Factors on Outcomes

Poisson regression was used to associate the continuous factors derived from the CFA results onto various count-based acute-care usage outcomes. These outcomes were divided into two main categories, emergency room (ER) visit records and inpatient hospital (IH) stay records. Within each subdivision, there were variables both measuring 1-year pre- and post- index date (the survey data generation date) of both hospital utilization variables, along with a 2-year total lag of both pre- and post- 1-year ER or IH stays. Generalized Linear Modeling Binary logistic regression was used to assess the full model of factors against two sets of dichotomous variables, All ER and All IH, which are both binary measures of Y = 0 no emergency room or inpatient hospital visits versus Y = 1 at least one or any ER or IH visits. To find the parsimonious binary logistic model, a backwards stepwise elimination binary logistic regression method was used to reduce the models to their most predictively effective form, consisting of predictors that are the most statistically significant when compared by observed significance levels (p-value).

RESULTS

Item-level Descriptive Statistics

Because all of the original survey items were dichotomous or Likert-based, they were bound by a range of response levels between 2 (dichotomous) to 10 (ordinal or interval) options. That is why in Table 0 the counts of respondents responding to each response level, and their percents from the total respondents that responded to each respective question, were given; along with how much missing data and the corresponding percents each item had. Also in the table, there were study-specific item names attributed to each item, but the actual survey item numbers and labels were also supplied. For the already validated questions, their original questionnaire origins were supplied, along with the official designation by the VA CDW if the variable was auto-generated; however, the variables that were project-specific include a hypothesized domain name that attributes to the latent factor intended on being measured when the items were created. See Table 0 in the Appendix.

Factor Analyses – Exploratory

The results of the exploratory factor analyses (EFA) are in Table 1. Geomin rotation – oblique type was used to rotate the multidimensional axes, to find the proposed factor-model that best fits the data, while also having a minimum of 0.400 factor loadings per item per factor. The best fitting model was determined by a combination of the results from parallel analysis, and the Kaiser criterion methods, along with a scree plot visual heuristic. These EFA results determined that a 17-factor model was best suited dimensionality of the data, and Table 1 shows the factor structure that each item falls into, along with all items having at least a 0.400 factor loading – factor loadings being the correlation of each item to its corresponding latent factor. See Table 1 in the Appendix.

Factor Analyses – Confirmatory

The results of the confirmatory factor analysis (CFA) to see if the model fits the HERO Care survey data well. This was assessed using several model fit indicators. The most popularly presented overall model fit indicator is the chi-square, where a non-significant test statistic indicates that the overall model fit the data well, where the opposite is true. It is noteworthy to mention that the Chi-square, though a very popular model fit assessment metric, is easily influenced by large study sample sizes, and therefore in the line of survey work, where samples sizes above 200 through at least 500 or 1,000+ are common, one's Chi-square is almost always statistically significant. This is more a reality of applied survey validation work and should not be weighed heavily when considering the appropriateness of the hypothesized factor model on the model-data.

The comparative fit index (CFI) and the Tucker-Lewis index (TLI) were calculated, where a threshold of at least 0.900 indicates moderate fit, and a 0.950 indicates a good fit – think of academic grade point averages. Root mean-square error approximation (RMSEA) and standardized root mean square residual (SRMR) were calculated, where the thresholds of at most 0.700 and 0.800 respectively indicate moderate fit and estimates below a 0.05 are considered – think p-value thresholds. For this study the Chi-square value was statistically significant ($\chi^2_{2713} = 14{,}304$) and the CFI and TLI suggested moderate fit (CFI = 0.900) and below moderate fit (TLI = 0.892) respectively. Yet, the estimates from both the RMSEA and SRMR suggest good model fit (RMSEA = 0.023, SRMR = 0.043). See Table 2 below for these results.

***Table 2*: Confirmatory factor analysis model fit results**

Estimation*	**Chi-square**	***df***	**CFI**	**TLI**	**RMSEA**	**SRMR**
ULSMV*	14304	2713	0.900	0.892	0.023	0.043

Note: Estimation method, unweighted least-squares mean-variance.

Factor & outcome-level descriptive statistics

Because the results of the confirmatory factor analysis led to confirming that the model fit the data well, factor scores were calculated using summated averages of each item's score that did not have a missing value. This led to the creation of continuous factors 1-17. Table 3-1 provides the factor abbreviations and descriptions, and Table 3-2 provides the items that made them up, the sample size of each factor with present data, and the usual continuous descriptors such as minimum, maximum, mean, standard error of the mean, and univariate normality assessors – skewness and kurtosis. It should be noted that the smallest set of complete values was for factor 13 with 4737 and the highest were factors 1 and 2 with 8033. Also, factors 1, 5, 7, 10, 13, and 17 were not univariate normal because they had a combination of skewness, kurtosis, or both that was above 2.00. The complete cases maximum across all items, and for the remainder of the following results below was 3,939.

***Table 3-1*: Factor abbreviations and descriptions**

Factors	Descriptions
TPN	Transportation: Transportation issues to getting healthcare

HS	Homebound Status: How homebound is the patient
SNI	Social Network Index: How big/small is the social network of patient
MDu	Mental Duress: Anxiety, depression, & feelings of loneliness
MI	Medication Insecurity: Skipping on/taking less medication b/c $
FI	Financial Insecurity: Deficiency on funds to survive & thrive
ADL	Activities of Daily Living: Disability measure of corporal independence
QoL	Quality of Life: Self-perceptions about aspects of patient's health
PE	Pain Exposure: Pain interfering w/ life, activities, & many meds for pain
MDf	Mobility Difficulty: Physical frailty, mobility, & falls
HM	Health Management: Self case management of healthcare needs
IADL	Instrumental Activities of Daily Living: Life management independence
C-19:RHC	Covid-19 Receiving Home Care: Ability to receive home-health services & care
IBT	Internet-Based Telecommunication: Affinity w/ + Frequency of Internet-use
C-19:EH	Covid-19: Emotional Health: positive & negative feelings
C-19:I	Covid-19: Isolation: Communication & time with loved ones, life satisfaction
SUD	Substance Abuse: Abuse of alcohol, smoking, illicit drugs

***Table 3-2*: Factor-level descriptive statistics, structure, and descriptive statistics of regression outcomes**

Factors	Items	Size*	Min	Max	Mean	SE	Skewness	Kurtosis
TPN*	TPS1, TPS2, TPS3	8033	0	1	0.1245	0.0032	2.2531	3.7464
HS	HBS1-HBS4	8035	0	3.5	2.0318	0.0092	-0.9643	-0.3815
SNI	SI1-SI4	7984	0	4	2.0893	0.0122	0.1170	-0.9395
MDu	SNN1, PHQ1, PHQ2, GAD1, GAD2	8021	0	3	1.0545	0.0056	1.0836	0.7829
MI*	MI1-MI3	7962	0	1	0.0304	0.0017	5.4453	29.7849
FI	FI1, FI2, FI3	7982	0	2.5	1.4857	0.0035	-0.0094	1.2938
ADL	DAHC1-DAHC8	7863	0	4	0.6163	0.0099	1.7477	2.8823
QoL	PM1-PM6	7936	0	4	1.9124	0.0102	0.1533	-0.5921
PE	PM10, PN2-PN4	7937	0	10	2.6993	0.0249	0.5062	-0.8271
MDf*	FS2, FS3, MF3, PM7	8020	0	4	1.0018	0.0031	1.1781	11.6718
HM	DAHC19-DAHC23	7828	0	4	0.9322	0.0123	1.0363	0.2648
IADL	DAHC10-DAHC15	7854	0	4	0.9957	0.0130	1.0706	0.2452
C-19: RHC*	CD2-CD5, CD7-CD8	4737	0	2	0.9769	0.0052	-0.1979	3.4013
IBT	TU3-TU6, TU8, TU10	7937	0	6	1.3693	0.0087	-0.1464	-1.1774

C-19: EH	CD14, CD16-CD18	5154	0	2	1.1976	0.0066	0.0023	0.3457
C-19: I	CD10-CD12	5573	0	2	0.7530	0.0066	0.1498	-0.0561
SUD*	SU3, CD20	7806	0	4	0.1238	0.0045	5.9702	45.5814

**Complete cases, 3939; Factors F1, F5, F10, F17 were not univariately normal.*

Once the factor scores were generated, they were regressed across a slew of acute-care utilization and unmet needs-related outcomes. This was done to assess the convergent validity of the factor structure of the HERO Care survey. Similar to Table 0, Table 4 provides the descriptive statistics of all of the study outcomes, divided by their auto-generated VA CDW repository names, their descriptions, and the counts with percents of their corresponding response levels. The several outcomes and their descriptions were mentioned above. Nevertheless, it is worth noting that because these variables were pulled from the official VA repository of Veteran patient medical records, there was no missing data across all the variables, thus aiding the statistical power of the estimated results. See Table 4 for these results.

***Table 4*: Outcome variable descriptions, measurement types, & distributions**

Variables*	Description	Counts	%
BaseER	The count of emergency room visits/records in the year prior to the index date	0 = 6240 1 = 640 2-5 = 913 6-54 = 263	0 = 77.5% 1 = 7.9% 2-5 = 11.4% 6-54 = 3.2%
FollowER	The count of emergency room visits/records in the year after to the index date	0 = 6315 1 = 642 2-5 = 874 6-102 = 225	0 = 78.4% 1 = 8.0% 2-5 = 5.9% 6-102 = 2.8%
BaseIH	The count of Inpatient stay records in the year prior to the index date	0 = 6607 1 = 766 2-3 = 508 4-15 = 175	0 = 82.0% 1 = 9.5% 2-3 = 6.3% 4-15 = 2.2%

FollowIH	The count of Inpatient stay records in the year following the index date	0 = 6576 1 = 809 2-3 = 480 4-15 = 191	0 = 81.6% 1 = 10.0% 2-3 = 6.0% 4-15 = 2.4%
TotalER	Two-year count of emergency room visits both one year before & after index date	0 = 5574 1 = 663 2-7 = 1426 8-156 = 393	0 = 69.2% 1 = 8.2% 2-7 = 17.7% 8-156 = 4.9%
TotalIH	Two-year count of inpatient stay records both one year before & after index date	0 = 5785 1 = 1009 2-5 = 1035 6-28 = 227	0 = 71.8% 1 = 12.5% 2-5 = 12.8% 6-28 = 2.9%
AnyER	Dichotomous measure of any emergency room visit records between both one year before & after index date	0 = 5574 1 = 2482	0 = 69.2% 1 = 30.8%
AnyIH	Dichotomous measure of any inpatient stay records between both one year before & after index date	0 = 5785 1 = 2271	0 = 71.8% 1 = 28.2%

**Variables, database data retrieved from Veterans Affairs (VA) Corporate Data Warehouse (CDW) matched by unique survey identifiers and index date of first wave of survey data collection*

Regressions – Poisson, GLM Binary Logistic, Backward Stepwise Binary Logistic

Because the outcomes Baseline ER, Follow-up ER, Baseline IH, Follow-up IH, Two-year ER and Two-year IH are count-based, Poisson regression was used to estimate the association of each validated factor score with each of them. To test if the full model of predictors (all factors 1-17 regressed on each outcome) fit the data well, several model-fit estimators were calculated. The Omnibus test, the Akaike information criteria, the Bayesian information criteria, and the -2-log-likelihood were estimated, where the Omnibus test indicates good model fit if the test statistic is statistically significant – it was for each of the Poisson models – and the last three operate on the model "smaller-is-better," where when comparing models, a lesser value of each metric indicates a better model fit when compared to other related models. It is worthy to refer to the confirmatory factor analysis mentioned above in that since there was only model confirmed, the model fit assessors mentioned for the regression analyses were not calculated because the 17-factor model was not compared to other models.

There were several confirmed factors that were significantly associated with the outcomes. Here they are divided into the three outcomes that represent emergency room (ER) visit records first, then the other inpatient hospital (IH) visit records second. Factors 1, 2, 7, 9-12, 14, 16, and 17 were statistically significantly associated with the 1-year baseline pre-index date ER records visits from survey index date. Factors 1, 6-11, 14, and 17 were statistically significantly associated with the 1-year follow-up post-index date ER records visits from survey index date. Factors 1-3, 6-11, 14, and 17 were statistically significantly associated with the 2-year total count of ER visits for both the pre-post-index date.

Regarding the count of inpatient hospital visits, the intercept, and factors 5, 14, 16-17 were statistically significantly associated the 1-year baseline pre-index date IH visit records visits from survey index date. The intercept, and factors 2, 11, 13-14, and 17 were statistically significantly associated the 1-year follow-up post-index date IH visit records visits from survey index date. The intercept, and factors 5, 8, 11, 13-14, and 16-17 were statistically significantly associated with the 2-year total count of pre-post-index date IH visit records. See Table 5 for the remaining statistical estimates regarding the Poisson regressions on the acute-care utilization outcomes.

Regarding the outcomes that were measured dichotomously, a generalized linear modeling (GLM) binary logistic regression was performed to regress the full model of each of the confirmed continuous factors on each of the binary outcomes. Recall that two outcomes were acute-care utilization based and two measured unmet needs. All ER was categorized by $Y = 0$, no ER visit records within the 2-year pre-post-index date, with $Y = 1$, any or at least 1 ER visit record within the 2-year pre-post-index date, and All IH was categorized by $Y = 0$, no IH visit records within the

2-year pre-post-index date, and Y = 1, any or at least 1 ER visit record within the 2-year pre-post-index date. The other two dichotomously measured outcomes were study-specific items whose latent traits intended to measure unmet needs, which is the phenomena of a deficit health and well-being related dimension of a patient's life whereby if it remains unfulfilled for too long, over time it has deleterious effects that cascade within themselves and their social and communal networks around them.

It suffices to say, which is beyond the scope of this paper, that unmet needs can be associated with needing healthcare and not being able to get it (which is how both items are relatively worded) and it adversely correlated with the patients' social capital. See Table 6 for the model fit comparisons between the full and parsimonious models of the aforementioned binary outcomes, full of the usual model fit culprits (AIC, BIC, -2LL) along with the Hosmer and Lemeshow test, the Omnibus Tests of Model Coefficients, for both the first step (baseline full model) and the last remaining step of the parsimonious model, within the Appendix.

Table 7 showcases the parsimonious models, using backward stepwise (likelihood ratio) elimination binary logistic regression, with an empirical variable selection strategy and a generalized linear modeling approach. The corresponding factor-level mean and standard deviations, Wald test statistics (with corresponding degrees of freedom and p-values) and effect size estimating odds ratios (also bound by corresponding 95% confidence intervals) were provided for each final step factor score, across the four outcomes. The resulting final models indicated that several factors were associated with any counts of acute-care usage or indications of unmet needs.

Regarding unmet needs about needing healthcare but not receiving it, the intercept, and factors 1-2, 4-5, 9, and 11-16 were statistically significantly associated with this outcome (HCN1). Regarding unmet needs about needing emotional health, mental health, and/or substance use related health services, and not receiving them, the intercept, and factors 2-3, 4-5, 8, 14-15 and 17 were statistically associated with this outcome (HCN2). Regarding the outcomes measuring any acute-care usage, the intercept and factor 17 was statistically significantly associated for both outcomes, but factor 14 was statistically significantly associated for the binary measure of any or at least one ER visit record within the two-year pre-post-index date, and factor 15 was statistically significantly associated for the binary measure of any or at least one IH visit record within the two-year pre-post-index date, respectively. See Table 7 in the Appendix for full regression results; see Table 8 for the heat-zone mapping of the odds ratios of each factor on each outcome.

DISCUSSION

Limitations & Strengths

There were a few study limitations and strengths. Both a strength and limitation of this survey was that the results are generalizable to Veterans across the geographic United States (including California, Utah, Texas, Florida, Puerto Rico, and New York) but also is limited to United States Veterans receiving care from the VA. Because of the nature of mailed and online surveys, these survey questions are secondary-data indications of health statuses and related measures that are indirectly measured and affected by recall bias and temporal effects such as the global Covid-19 pandemic that affected everyone on the planet, directly or otherwise.

It is also important to note that these limitations are to be accepted as usual limitations of survey analyses – that factor analyses and survey results usually hover around the domain of correlations and associations, not causations – yet this, and that the pandemic affected everyone, are commonly accepted limitations in practice. As mentioned above, this study has more strengths such as the proven validity of the HERO Care survey as a psychometrically validated measurement tool, that measures its intended constructs, and converges towards real-world applicable outcomes that affect Veterans and the VA health system in real time.

Policy Recommendations

Despite these limitations and improving upon the strengths of this research, this current study is of many to be executed using this cross-section of data. While the last timewave of data is being collected, it precedes a large body of work to be written hereafter. These novel results have very strong indications of ways to quantify the needs of Veterans, towards addressing the unmet needs of our ever-increasing ageing and vulnerable populations, both as part of the VA health system, and with future implications for this endeavor to be replicated within the context of Centers for Medicare & Medicaid Services (CMS) health system population.

We recommend the health factors related to transportation access to healthcare, homebound status, quality of life, pain exposure, a patient's own healthcare management, and internet-based telecommunication proficiency should be explored when intervening to reduce a Veteran patient's acute-care usage and unmet needs. This recommendation is supported by our findings which illustrate that these health factors are all statistically significantly associated to over half of the study outcomes. Regarding the study outcomes, we found that base, follow-up, and total emergency room stays (ERS), total inpatient hospital stays (IHS), and both unmet needs (healthcare and mental health) are adverse health system and patient outcomes that are statistically significantly associated with over half of the study outcomes. Therefore, we suggest implementing the results of this study towards policy that addresses these health factors, which would conversely aide in lessening the burden of these aforementioned study outcomes.

CONCLUSION

In an effort to identify the unmet needs of Veterans and their caregivers within their communities, several Veteran Affairs Medical Centers (VAMC), the Geriatrics Extended Care Data Analysis Center (GECDAC), and the Elizabeth Dole Center for Excellence in Veteran and Caregiver Research (EDCoE), among other stakeholders, collaborated to create the Home Excellence Resource Center to Advance, Redefine, and Evaluate Non-Institutional Care (HERO Care) survey. The GECDAC identified a sample of 20,000 Veterans to have surveys either mailed or electronically given to them and their caregivers, where this study's sample is a cross-section of 8,056 Veterans from the first timewave of data collection. Using factor analysis and regression, we found a 17-health-factor model fit the data adequately, where the health factors transportation access to healthcare, homebound status, quality of life, pain exposure, a patient's own healthcare management, and internet-based telecommunication proficiency were statistically significantly associated with base, follow-up, and total emergency room stays (ERS), total inpatient hospital stays (IHS), and both unmet needs (healthcare and mental health). We recommend closer examination of these relationships towards promoting policy that designates resources to supplement health and governing systems to address these health factors, which may lessen the health system and patient burdens of acute-care usage and unmet needs.

APPENDIX

***Table 0*: HERO Care survey item descriptions, frequencies, & missingness**

Items	Domain	Description	Item Status*	Count (%)	Missing (%)
TPS1	Transportation	3. Has lack of transportation kept you from medical appointments, meetings, work, or from getting things needed for daily living? Select all that apply. - No	NACHC PRAPARE	0 = 1013(12.6%) 1 = 6987(86.7%)	56(0.70%)
TPS2		3. Has lack of transportation kept you from medical appointments, meetings, work, or from getting things needed for daily living? Select all that apply. - Yes, it has kept me from medical appointments or from getting my medications		0 = 7264(90.2%) 1 = 736(9.1%)	56(0.70%)
TPS3		3. Has lack of transportation kept you from medical appointments, meetings, work, or from getting things needed for daily living? Select all that apply. - Yes, it has kept me from non-medical meetings, appointments, work, or from getting things that I need		0 = 6760(83.9%) 1 = 1194(14.8%)	102(1.3%)
HBS1	Homebound Status	5. In the last month, how often did you leave your home to go outside?	NHATS MOBILITY SECTION	0 = 231(29%) 1 = 935(11.6%) 2 = 1433(17.8%) 3 = 1539(19.1%) 4 = 3821(47.4%)	97 (1.2%)
HBS2		6. In the last month, did anyone ever help you leave your home to go outside?		0 = 2370(29.4%) 1 = 5606(69.6%)	80(1.0%)

HBS3		7. In the last month, when you left your home to go outside, how often did you do this by yourself?		0 = 1183(14.7%) 1 = 521(6.5%) 2 = 762(9.5%) 3 = 5433(67.4%)	157(1.9%)
HBS4		8. In the last month, how much difficulty did you have leaving your home to go outside by yourself?		0 = 1085(13.5%) 1 = 1002(12.4%) 2 = 1382(17.2%) 3 = 4396(54.6%)	191(2.4%)
MN1	Mobility Need	9. In the last month, did you ever have to stay in your home because no one was there to help you go out, or you had difficulty going out by yourself?		0 = 1117(13.9%) 1 = 6806(84.5%)	133(1.7%)
SI1	Social Index	10. In a typical week, how many times do you talk on the telephone with family, friends, or neighbors?	Berkman–Syme Social Network Index	0 = 351(4.4%) 1 = 1111(13.8%) 2 = 945(11.7%) 3 = 1087(13.5%) 4 = 4425(54.9%)	137(1.7%)
SI2		11. In a typical week, how often do you get together with friends or relatives?		0 = 892(11.1%) 1 = 1881(23.3%) 2 = 1556(19.3%) 3 = 1249(15.5%) 4 = 2328(28.9%)	150(1.9%)
SI3		12. How often do you attend church or religious services?		0 = 3703(46.0% 1 = 673(8.4%) 2 = 391(4.9%) 3 = 228(2.8%) 4 = 2732(33.9%)	329(4.1%)
SI4		13. How often do you attend meetings of the clubs or organizations you belong to such as, church group, union, fraternal or athletic group, or school group?		0 = 4626(57.4%) 1 = 513(6.4%) 2 = 362(4.5%) 3 = 221(2.7%) 4 = 2132(26.5%)	202(2.5%)

SNN1	Social Network Need	14. How often do you feel lonely or isolated from those around you?	Study-specific	0 = 3085(38.3%) 1 = 1767(21.9%) 2 = 2615(32.5%) 3 = 438(5.4%)	151(1.9%)
SSN2	Social Support Need	15. How often do you get the social and emotional support you need?	Study-specific	0 = 561(7.0%) 1 = 745(9.2%) 2 = 1687(20.9%) 3 = 2303(28.6%) 4 = 2583(32.1%)	177(2.2%)
MI1	Medication Insecurity	16. In the last 12 months, did you skip medication doses to save money?	MEDICAL EXPENDITURE PANEL SURVEY	0 = 7709(95.7%) 1 = 222(2.8%)	125(1.6%)
MI2		17. In the last 12 months, did you take less medicine to save money?		0 = 7700(95.6%) 1 = 237(2.9%)	119(1.5%)
MI3		18. In the last 12 months, did you delay filling a prescription to save money?		0 = 7677(95.3%) 1 = 260(3.2%)	119(1.5%)
FI1	Financial Insecurity	19. Within the last 12 months, you have worried that your food would run out before you got money to buy more.	2-ITEM FOOD INSECURITY SCREEN VALIDATED COMPARED TO THE US Department of Agriculture 18-item Household Food Security Survey (HFSS)	0 = 203(2.5%) 1 = 896(11.1%) 2 = 6832(84.8%)	125(1.6%)
FI2		20. Within the last 12 months, the food you bought just didn't last and you didn't have enough money to get more.		0 = 157(1.9%) 1 = 803(10.0%) 2 = 6984(86.7%)	112(1.4%)
FS1	Financial Situation	21. Without giving exact dollars, how would you describe your household's financial situation right now? Would you say that:	NLTCS	0 = 3894(48.3%) 1 = 2170(26.9%) 2 = 665(8.3%) 3 = 255(3.2%)	1072(13.3%)

NS1	Neighborhood Safety	24. How safe from crime do you consider your neighborhood to be?	Study-specific	0 = 2691(33.4%) 1 = 4103(50.9%) 2 = 731(9.1%) 3 = 147(1.8%)	384(4.8%)
HCN1	Unmet Healthcare Need	27. During the past 12 months, was there ever a time when you felt you needed healthcare but didn't receive it?	CCHS Cyce 3.1	0 = 6351(78.8%) 1 = 1360(16.9%)	345(4.3%)
HCN2		28. During the past 12 months, was there ever a time when you felt that you needed help for your emotions, mental health, or use of alcohol or drugs, but you didn't receive it?	Canadian Community Health Survey	0 = 6038(75.0%) 1 = 720(8.9%)	1298(16.1%)
PHQ1	Depression	30. Little interest or pleasure in doing things	PHQ-2	0 = 4193(52.0%) 1 = 1974(24.5%) 2 = 828(10.3%) 3 = 892(11.1%)	169(2.1%)
PHQ2		31. Feeling down, depressed, or hopeless		0 = 4727(58.7%) 1 = 2125(26.4%) 2 = 556(6.9%) 3 = 474(5.9%)	174(2.2%)
GAD1	Anxiety	32. Feeling nervous, anxious or on edge	GAD	0 = 4684(58.1%) 1 = 2151(26.7%) 2 = 546(6.8%) 3 = 469(5.8%)	206(2.6%)
GAD2		33. Not being able to stop or control worrying		0 = 4911(61.0%) 1 = 1958(24.3%) 2 = 496(6.2%) 3 = 477(5.9%)	214(2.7%)

RL1	Resiliency	34. I am able to adapt when changes occur.	CDRISC-2	0 = 574(7.1%) 1 = 653(8.1%) 2 = 1703(21.1%) 3 = 2058(25.5%) 4 = 2927(36.3%)	141(1.8%)
RL2		35. I tend to bounce back after illness, injury, or other hardships.		0 = 359(4.5%) 1 = 423(5.3%) 2 = 1598(19.8%) 3 = 2512(31.2%) 4 = 3013(37.4%)	151(1.9%)
FS1	Frailty	36. How much of the time during the past 4 weeks did you feel tired?	5-item Frail Scale	0 = 973(12.1%) 1 = 1886(23.4%) 2 = 2824(35.1%) 3 = 1790(22.2%) 4 = 472(5.9%)	111(1.4%)
FS2		37. Do you have any difficulty walking up 10 steps (stairs) without resting and without using aids?		0 = 3428(42.6%) 1 = 4445(55.2%)	183(2.3%)
FS3		38. Do you have any difficulty walking a couple of blocks (e.g. several hundred yards) alone without aids?		0 = 3075(38.2%) 1 = 4830(60.0%)	151(1.9%)
FS5g		5lb loss in weight without your shoes from last year to this year		0 = 833(10.3%) 1 = 6770(84.0%)	453(5.6%)
MF1	Mobility/Falls	41. Did you have any falls within the last 12 months?	Study-specific	0 = 4099(50.9%) 1 = 1265(15.7%) 2 = 1020(12.7%) 3 = 608(7.5%) 4 = 274(3.4%) 5 = 630(7.8%)	160(2.0%)
MF2	Mobility/Falls	42. Did you need any medical attention at the ER or by medical		0 = 2901(36.0%) 1 = 653(8.1%) 2 = 1316(16.3%)	3186(39.5%)

		provider for any of these falls in the last 12 months?			
MF3	Mobility/Falls	43. Do you use any assistive devices such as a cane, walker, or wheelchair?		0 = 3684(45.7%) 1 = 4187(52.0%)	185(2.3%)
PM1	Quality of Life	45. The following questions ask about different aspects of your health and functioning. In general... - would you say your health is:		0 = 785(9.7%) 1 = 2482(30.8%) 2 = 2849(35.4%) 3 = 1485(18.4%) 4 = 269(3.3%)	186(2.3%)
PM2	Quality of Life	45. The following questions ask about different aspects of your health and functioning. In general... - would you say your quality of life is:		0 = 457(5.7%) 1 = 1809(22.5%) 2 = 2945(36.6%) 3 = 1931(24.0%) 4 = 658(8.2%)	256(3.2%)
PM3	Quality of Life	45. The following questions ask about different aspects of your health and functioning. In general... - how would you rate your physical health?	PROMIS-10	0 = 929(11.5%) 1 = 2622(32.5%) 2 = 2644(32.8%) 3 = 1285(16.0%) 4 = 247(3.1%)	329(4.1%)
PM4	Quality of Life	45. The following questions ask about different aspects of your health and functioning. In general... - how would you rate your mental health, including your mood and your ability to think?		0 = 767(9.5%) 1 = 1748(21.7%) 2 = 2378(29.5%) 3 = 1958(24.3%) 4 = 996(12.4%)	209(2.6%)
PM5	Quality of Life	45. The following questions ask about different aspects of your health and functioning. In general... - how would you rate your satisfaction with your social activities and relationships?		0 = 951(11.8%) 1 = 1870(23.2%) 2 = 2455(30.5%) 3 = 1699(21.1%) 4 = 866(10.7%)	215(2.7%)

PM6	Quality of Life	45. The following questions ask about different aspects of your health and functioning. In general... - please rate how well you carry out your usual social activities and roles. (This includes activities at home, work and in your community, and responsibilities as a parent, child, spouse, employee, friend, etc.)		0 = 931(11.6%) 1 = 1728(21.4%) 2 = 2442(30.3%) 3 = 1856(23.0%) 4 = 811(10.1%)	288(3.6%)
PM7	Quality of Life	46. To what extent are you able to carry out your everyday physical activities such as walking, climbing stairs, carrying groceries, or moving a chair?		0 = 904(11.2%) 1 = 1579(19.6%) 2 = 1830(22.7%) 3 = 1463(18.2%) 4 = 2109(26.2%)	171(2.1%)
PM8	Quality of Life	47. In the past 7 days, how often have you been bothered by emotional problems such as feeling anxious, depressed or irritable?		0 = 281(3.5%) 1 = 902(11.2%) 2 = 2215(27.5%) 3 = 2080(25.8%) 4 = 2420=(30.0%)	158(2.0%)
PM9	Quality of Life	48. In the past 7 days, how would you rate your fatigue on average?		0 = 846(10.5%) 1 = 2442(30.3%) 2 = 3357(41.7%) 3 = 975(12.1%) 4 = 234(2.9%)	202(2.5%)

PM10	Quality of Life	49a. How would you rate your pain on average?		0 = 1204(14.9%) 1 = 784(9.7%) 2 = 812(10.1%) 3 = 1013(12.6%) 4 = 858(10.7%) 5 = 919(11.4%) 6 = 662(8.2%) 7 = 706(8.8%) 8 = 505(6.3%) 9 = 187(2.3%) 10 139(1.7%)	267(3.3%)
PN2	Pain Need	49b. What number best describes how, during the past week, pain has interfered with your enjoyment of life?	Study-specific	0 = 2354(29.2%) 1 = 752(9.3%) 2 = 668(8.3%) 3 = 695(8.6%) 4 = 582(7.2%) 5 = 741(9.2%) 6 = 492(6.1%) 7 = 499(6.2%) 8 = 461(5.7%) 9 = 237(2.9%) 10 = 337(4.2%)	238(3.0%)
PN3	Pain Need	49c. What number best describes how, during the past week, pain has interfered with your general activity?		0 = 2332(28.9%) 1 = 820(10.2%) 2 = 715(8.9%) 3 = 702(8.7%) 4 = 569(7.1%) 5 = 692(8.6%) 6 = 482(6.0%) 7 = 498(6.2%) 8 = 431(5.4%) 9 = 267(3.3%) 10 = 344(4.3%)	204(2.5%)

PN4	Pain Need	50. If you are experiencing any pain, are you taking any prescribed medication for pain?		0 = 4680(58.1%) 1 = 3036(37.4%)	340(4.2%)
DAHC1	Daily Activities & Health Care Needs	51. Do you need help with... - bathing or showering?		0 = 4528(56.2%) 1 = 1415(17.6%) 2 = 958(11.9%) 3 = 365(4.5%) 4 = 431(5.4%)	359(4.5%)
DAHC2	Daily Activities & Health Care Needs	51. Do you need help with... - getting dressed or changing clothes?		0 = 4606(57.2%) 1 = 1477(18.3%) 2 = 939(11.7%) 3 = 362(4.5%) 4 = 340 (4.2%)	332(4.1%)
DAHC3	Daily Activities & Health Care Needs	51. Do you need help with... - eating or drinking?		0 = 5244(65.1%) 1 = 1539(19.1%) 2 = 559(6.9%) 3 = 197(2.4%) 4 (113(1.4%)	404(5.0%)
DAHC4	Daily Activities & Health Care Needs	51. Do you need help with... - getting in and out of the bed or chairs? (use of mechanical transfer aids are acceptable)	Barthel's Activities of Daily Living	0 = 4579(56.8%) 1 = 1897(23.5%) 2 = 692(8.6%) 3 = 342(4.2%) 4 = 238(3.0%)	308(3.8%)
DAHC5	Daily Activities & Health Care Needs	51. Do you need help with... - using the toilet?		0 = 5013(62.2%) 1 = 1800(22.3%) 2 = 479(5.9%) 3 = 190(2.4%) 4 = 231(2.9%)	343(4.3%)
DAHC6	Daily Activities & Health Care Needs	51. Do you need help with... - managing incontinence or changing diapers?		0 = 5198(64.5%) 1 = 1174(14.6%) 2 = 578(7.2%) 3 = 203(2.5%) 4 = 289(3.6%)	614(7.6%)

DAHC7	Daily Activities & Health Care Needs	51. Do you need help with... - walking across a small room?		0 = 4854(60.3%) 1 = 1673(20.8% 2 = 579(7.2%) 3 = 207(2.6%) 4 = 346(4.3%)	397(4.9%)
DAHC8	Daily Activities & Health Care Needs	51. Do you need help with... - brushing your teeth or dentures?		0 = 5563(69.1%) 1 = 1495(18.6%) 2 = 358(4.4%) 3 = 123(1.5%) 4 = 146(1.8%)	371(4.6%)
DAHC9	Daily Activities & Health Care Needs	51. Do you need help with... - using the telephone, including looking up numbers and dialing?		0 = 4951(61.5%) 1 = 1286(16.0%) 2 = 767(9.5%) 3 = 300(3.7%) 4 = 414(5.1%)	338(4.2%)
DAHC10	Daily Activities & Health Care Needs	51. Do you need help with... - transportation, either by having someone drive you or help you get transportation?	Lawton's Instrumental Activities of Daily Living	0 = 4484(55.7%) 1 = 771(9.6%) 2 = 1397(17.3%) 3 = 392(4.9%) 4 = 663(8.2%)	349(4.3%)
DAHC11	Daily Activities & Health Care Needs	51. Do you need help with... - grocery shopping or other shopping?		0 = 4088(50.7%) 1 = 920(11.4%) 2 = 1584(19.7%) 3 = 334(4.1%) 4 = 702(8.7%)	428(5.3%)
DAHC12	Daily Activities & Health Care Needs	51. Do you need help with... - preparing meals?		0 = 3879(48.2%) 1 = 1034(12.8%) 2 = 1522(18.9%) 3 = 369(4.6%) 4 = 729(9.0%)	523(6.5%)

DAHC13	Daily Activities & Health Care Needs	51. Do you need help with... - housework such as doing dishes or laundry?		0 = 3895(48.3%) 1 = 1059(13.1%) 2 = 1516(18.8%) 3 = 396(4.9%) 4 = 736(9.1%)	454(5.6%)
DAHC14	Daily Activities & Health Care Needs	51. Do you need help with... - handling money or paying bills?		0 = 4407(54.7%) 1 = 1097(13.6%) 2 = 1364(16.9%) 3 = 219(2.7%) 4 = 531(6.6%)	438(5.4%)
DAHC15	Daily Activities & Health Care Needs	51. Do you need help with... - taking medicine like pills or eye drops in the right dose at the right time?		0 = 4441(55.1%) 1 = 1186(14.7%) 2 = 1311(16.3%) 3 = 281(3.5%) 4 = 499(6.2%)	338(4.2%)
DAHC16	Daily Activities & Health Care Needs	51. Do you need help with... - taking injections in the right dose at the right time?		0 = 5240(65.0%) 1 = 623(7.7%) 2 = 716(8.9%) 3 = 112(1.4%) 4 = 350(4.3%)	1015(12.6%)
DAHC17	Daily Activities & Health Care Needs	51. Do you need help with... - managing your pain?		0 = 3569(44.3%) 1 = 1736(21.5%) 2 = 1098(13.6%) 3 = 631(7.8%) 4 = 509(6.3%)	513(6.4%)
DAHC18	Daily Activities & Health Care Needs	51. Do you need help with... - nursing or medical tasks in the home? (This might include wound care, tube feeding, caring for your ostomy, or operating equipment like oxygen tanks, nebulizers, or suctioning tubes.	Study-specific	0 = 5068(62.9%) 1 = 706(8.8%) 2 = 938(11.6%) 3 = 227(2.8%) 4 = 349(4.3%)	768(9.5%)

DAHC19	Daily Activities & Health Care Needs	51. Do you need help with... - communicating with health care professionals like doctors, nurses, or social workers about your care?	0 = 4309(53.5%) 1 = 1112(13.8%) 2 = 1386(17.2%) 3 = 427(5.3%) 4 = 458(5.7%)	364(4.5%)
DAHC20	Daily Activities & Health Care Needs	51. Do you need help with... - monitoring the severity of your health condition so treatment can be adjusted when needed?	0 = 3953(49.1%) 1 = 1161(14.4%) 2 = 1509(18.7%) 3 = 554(6.9%) 4 = 454(5.6%)	425(5.3%)
DAHC21	Daily Activities & Health Care Needs	51. Do you need help with... - getting information about your health condition(s)?	0 = 3950(49.0%) 1 = 1123(13.9%) 2 = 1580(19.6%) 3 = 555(6.9%) 4 = 461(5.7%)	387(4.8%)
DAHC22	Daily Activities & Health Care Needs	51. Do you need help with... - getting information on treatment (i.e. medication)?	0 = 3919(48.6%) 1 = 1068(13.3%) 2 = 1621(20.1%) 3 = 591(7.3%) 4 = 458(5.7%)	399(5.0%)
DAHC23	Daily Activities & Health Care Needs	51. Do you need help with... - any legal advice?	0 = 5292(65.7%) 1 = 676(8.4%) 2 = 953(11.8%) 3 = 307(3.8%) 4 = 395(4.9%)	433(5.4%)
DAHC24	Daily Activities & Health Care Needs	51. Do you need help with... - your housing situation?	0 = 5501(68.3%) 1 = 742(9.2%) 2 = 867(10.8%) 3 = 248(3.1%) 4 = 325(4.0%)	373(4.6%)

SU2	Substance Use	52. How many times in the past 12 months have you... - used tobacco products (like cigarettes, cigars, snuff, chew, electronic cigarettes)?		0 = 6854(85.1%) 1 = 189(2.3%) 2 = 58(0.7%) 3 = 82(1.0%) 4 = 629(7.8%)	244(3.0%)
SU3	Substance Use	52. How many times in the past 12 months have you... - used prescription drugs for non-medical reasons?		0 = 7492(93.0%) 1 = 127(1.6%) 2 = 13(0.2%) 3 = 17(0.2%) 4 = 129(1.6%)	278(3.5%)
SU4	Substance Use	52. How many times in the past 12 months have you... - used illegal drugs?		0 = 7550(93.7%) 1 = 99(1.2%) 2 = 23(0.3%) 3 = 26(0.3%) 4 = 68(0.8%)	290(3.6%)
TU3	Technology Use	55. How often do you use the Internet?		0 = 2433(30.2%) 1 = 315(3.9%) 2 = 91(1.1%) 3 = 361(4.5%) 4 = 154(1.9%) 5 = 976(12.1%) 6 = 3503(43.5%)	223(2.8%)
TU4	Technology Use	56. How confident are you in using the Internet?	Study-specific	0 = 2478(30.8%) 1 = 999(12.4%) 2 = 1650(20.5%) 3 = 1654(20.5%) 4 = 961(11.9%)	314(3.9%)
TU5	Technology Use	57. In the last 30 days, how often did you use the Internet to get information about your health conditions?		0 = 4962(61.6%) 1 = 1332(16.5%) 2 = 569(7.1%) 3 = 705(8.8%) 4 = 264(3.3%)	224(2.8%)

TU6	Technology Use	58. Have you ever had an appointment with a doctor, nurse, or other health professional, by video?		0 = 3883(48.2%) 1 = 3993(49.6%)	180(2.2%)
TU7	Technology Use	59. Would you be interested in having a video visit with a VA provider?		0 = 3412(42.4%) 1 = 2627(32.6%) 2 = 1770(22.0%)	247(3.1%)
TU8	Technology Use	60. Do you have a camera, attached or built into a computer, tablet, or other mobile device AND an Internet connection?		0 = 3031(37.6%) 1 = 4712(58.5%)	313(3.9%)
TU10	Technology Use	62. Would you be able to connect to a video visit, either by yourself or with the help of a friend or family member?		0 = 2238(27.8%) 1 = 3190(39.6%) 2 = 1278(15.9%) 3 = 1009(12.5%)	341(4.2%)
CD1	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Access to healthcare (i.e., urgent care, surgical procedure, diagnostic or medical screening test, treatment for an ongoing condition, regular check-up)		0 = 1165(14.5%) 1 = 2788(34.6%) 2 = 505(6.3%)	3598(44.7%)
CD2	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Ability to receive home nurse care (i.e., wound/ostomy care)	COVID-IMPACT	0 = 152(1.9%) 1 = 1664(20.7%) 2 = 161(2.0%)	6079(75.5%)
CD3	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Ability to receive homemaker services (i.e., cooking/cleaning)		0 = 176(2.2%) 1 = 1559(19.4%) 2 = 167(2.1%)	6154(76.4%)
CD4	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Ability to receive home		0 = 156(1.9%) 1 = 1535(19.1%) 2 = 172(2.1%)	6193(76.9%)

		health aide services (i.e., bathing/dressing)			
CD5	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Ability to receive home therapy services (i.e., physical/occupational/speech therapy)		0 = 220(2.7%) 1 = 1540(19.1%) 2 = 191(2.4%)	6105(75.8%)
CD6	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Timeliness of communication with providers		0 = 854(10.6%) 1 = 2734(33.9%) 2 = 336(4.2%)	4132(51.3%)
CD7	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Ability to obtain medication		0 = 274(3.4%) 1 = 3778(46.9%) 2 = 194(2.4%)	3810(47.3%)
CD8	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Ability to obtain needed care from a friend or family caregiver		0 = 298(3.7%) 1 = 2782(34.5%) 2 = 260(3.2%)	4716(58.5%)
CD9	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Financial problems for you or your family		0 = 161(2.0%) 1 = 2648(32.9%) 2 = 607(7.5%)	4640(57.6%)
CD10	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Communication with family or friends		0 = 849(10.5%) 1 = 3249(40.3%) 2 = 312(3.9%)	3646(45.3%)
CD11	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Time spent with friends or family		0 = 2196(27.3%) 1 = 2463(30.6%) 2 = 409(5.1%)	2988(37.1%)

CD12	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - General satisfaction with life	0 = 1518(18.8%) 1 = 3314(41.1%) 2 = 361(4.5%)	2863(35.5%)
CD13	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Difficulty sleeping	0 = 457(5.7%) 1 = 3329(41.3%) 2 = 1216(15.1%)	3054(37.9%)
CD14	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Feeling angry or irritated	0 = 269(3.3%) 1 = 3067(38.1%) 2 = 1170(14.5%)	3550(44.1%)
CD15	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Feeling happy	0 = 1197(14.9%) 1 = 3722(46.2%) 2 = 249(3.1%)	2888(35.8%)
CD16	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Feeling nervous, anxious or on edge	0 = 323(4.0%) 1 = 3020(37.5%) 2 = 1320(16.4%)	3393(42.1%)
CD17	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Feeling lonely or isolated	0 = 294(3.6%) 1 = 2948(36.6%) 2 = 1329(16.5%)	3485(43.3%)
CD18	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Feeling down, depressed or hopeless	0 = 257(3.2%) 1 = 3011(37.4%) 2 = 1133(14.1%)	3655(45.4%)
CD19	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Alcohol consumption	0 = 215(2.7%) 1 = 2017(25.0%) 2 = 206(2.6%)	5618(69.7%)
CD20	COVID19	72. Have YOU been affected by any of the following as a result of COVID-19? - Use of illegal drugs	0 = 64(0.8%) 1 = 1122(13.9%) 2 = 42(0.5%)	6828(84.8%)

Notes: Item statuses are pre-validated, study-specific, or auto-generated. Pre-validated, items taken from questionnaires that have already been proven to psychometrically measure their intended latent factors, under given contexts of types of respondents, measures, location, and time period, to name a few. Study-specific items were generated for the original purpose of this project, intended to measure constructs related to those of interest to this study, and to be validated within this context. Auto-generated items are not originally survey items asked in the original questionnaire but were downloaded from medical records within the Veteran Affairs (VA) Corporate Data Warehouse (CDW).

Table 1: **Exploratory factor analysis results with Geomin rotated factor loadings > 0.4, producing a 17-factor model**

Item/Factor	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
TPS1	-0.942																
TPS2	0.848																
TPS3	0.558																
HBS1		0.412															
HBS2		0.514															
HBS3		0.68															
HBS4		0.461															
~~MN1~~																	
SI1			0.434														
SI2			0.522														
SI3			0.506														
SI4			0.54														
SNN1				0.508													
~~SSN2~~																	
MI1					0.812												
MI2					0.86												
MI3					0.752												
FI1						-0.816											
FI2						-0.829											
FI3						0.588											
~~NS1~~																	
~~HCN1~~																	
~~HCN2~~																	
PHQ1				0.58													
PHQ2				0.819													
GAD1				0.776													
GAD2				0.787													
~~RL1~~																	
~~RL2~~																	

~~FS1~~						
FS2					0.643	
FS3					0.713	
~~FS5G~~						
~~MF1~~						
~~MF2~~						
MF3					0.615	
PM1			0.764			
PM2			0.64			
PM3			0.763			
PM4			0.473			
PM5			0.477			
PM6			0.526			
PM7					-0.412	
PM8	-0.711					
~~PM9~~						
PM10				0.855		
PN2				0.918		
PN3				0.907		
PN4				0.417		
DAHC1		0.688				
DAHC2		0.754				
DAHC3		0.762				
DAHC4		0.811				
DAHC5		0.987				
DAHC6		0.819				
DAHC7		0.673				
DAHC8		0.796				
~~DAHC9~~						
DAHC10						0.457
DAHC11						0.756

DAHC12		0.828			
DAHC13		0.795			
DAHC14		0.595			
DAHC15		0.433			
~~DAHC16~~					
~~DAHC17~~					
~~DAHC18~~					
DAHC19	0.744				
DAHC20	0.809				
DAHC21	0.923				
DAHC22	0.892				
DAHC23	0.521				
~~DAHC24~~					
~~SU1~~					
~~SU2~~					
SU3					0.415
TU3				0.76	
TU4				0.743	
TU5				0.562	
TU6				0.446	
~~TU7~~					
TU8				0.619	
TU10				-0.569	
~~CD1~~					
CD2			0.7		
CD3			0.755		
CD4			0.862		
CD5			0.711		
~~CD6~~					
CD7			0.406		
CD8			0.436		

~~CD9~~	
CD10	0.587
CD11	0.76
CD12	0.644
~~CD13~~	
CD14	0.652
~~CD15~~	
CD16	0.736
CD17	0.761
CD18	0.755
~~CD19~~	
CD20	1.004

***Table 5*: Poisson regression model fit and results of confirmed factors by acute-care outcomes**

Emergency Room Visits by Index Date				**Inpatient Hospital Visits by Index Date**			
Baseline ER (1-year pre-index date; *n*=3939)				**Baseline IH (1-year pre-index date; n=3939)**			
Omnibus	*AIC*	*BIC*	*-2LL*	*Omnibus*	*AIC*	*BIC*	*-2LL*
183.528***	13263.006	13376.022	-6613.503	67.623***	7131.047	7244.063	-3547.524
Poisson	*Wald*	*OR*	*95% CI OR*	*Poisson*	*Wald*	*OR*	*95% CI OR*
Intercept	0.039	0.816	(0.666, 1.394)	Intercept*	24.448	0.263	(0.155, 0.447)
F1*	9.377	0.856	(0.717, 0.929)	F1	1.928	0.879	(0.733, 1.054)
F2*	23.365	0.984	(0.803, 0.912)	F2	0.840	0.958	(0.874, 1.050)
F3	0.688	0.978	(0.948, 1.022)	F3	0.008	0.997	(0.945, 1.053)
F4	0.211	0.924	(0.891, 1.074)	F4	0.606	1.054	(0.923, 1.204)
F5	0.434	0.942	(0.729, 1.170)	F5*	10.098	1.563	(1.187, 2.059)
F6	0.959	0.778	(0.836, 1.062)	F6	0.463	0.943	(0.797, 1.116)
F7*	54.112	1.052	(0.727, 0.832)	F7	1.058	0.953	(0.868, 1.045)
F8	2.506	1.036	(0.988, 1.120)	F8	3.287	1.088	(0.993, 1.192)
F9*	13.231	0.825	(1.017, 1.056)	F9	3.734	1.028	(1.000, 1.057)
F10*	7.176	1.014	(0.717, 0.950)	F10	2.114	0.861	(0.703, 1.054)
F11*	0.278	1.093	(0.963, 1.068)	F11	0.506	1.027	(0.954, 1.106)
F12*	8.957	0.946	(1.031, 1.158)	F12	1.289	1.050	(0.965, 1.142)
F13	0.882	1.220	(0.843, 1.062)	F13	0.000	1.000	(0.849, 1.178)
F14*	55.460	0.933	(1.157, 1.285)	F14*	6.220	1.100	(1.021, 1.186)
F15	2.238	1.101	(0.852, 1.022)	F15	0.384	0.960	(0.843, 1.093)
F16*	4.690	1.243	(1.009, 1.201)	F16*	7.255	1.184	(1.047, 1.339)
F17*	38.490	1.171	(1.161, 1.332)	F17*	35.561	1.324	(1.207, 1.451)
Follow-up ER (1-year post-index date; *n*=3939)				**Follow-up IH (1-year post-index date; n=3939)**			
Omnibus	*AIC*	*BIC*	*-2LL*	*Omnibus*	*AIC*	*BIC*	*-2LL*
112.896***	13132.565	13245.581	-6548.282	49.048***	7452.808	7565.824	-3708.404
Poisson	*Wald*	*OR*	*95% CI OR*	*Poisson*	*Wald*	*OR*	*95% CI OR*
Intercept	0.016	0.976	(0.671, 1.421)	Intercept*	17.570	0.331	(0.198, 0.555)
F1*	5.120	0.861	(0.756, 0.980)	F1	2.136	0.874	(0.730, 1.047)

F2*	18.933	0.867	(0.813, 0.925)	F2*	3.153	0.922	(0.844, 1.008)
F3*	9.197	0.942	(0.906, 0.979)	F3	0.002	0.999	(0.947, 1.053)
F4	1.457	1.060	(0.965, 1.164)	F4	0.029	1.011	(0.887, 1.153)
F5	0.059	0.972	(0.771, 1.224)	F5	2.316	1.261	(0.935, 1.701)
F6*	9.148	0.828	(0.733, 0.936)	F6	1.536	0.899	(0.760, 1.064)
F7*	24.869	0.843	(0.788, 0.902)	F7	1.581	0.944	(0.862, 1.033)
F8*	6.380	1.087	(1.019, 1.160)	F8	1.743	1.062	(0.971, 1.160)
F9*	6.300	1.025	(1.006, 1.046)	F9	0.830	0.987	(0.961, 1.015)
F10*	3.548	0.872	(0.756, 1.006)	F10	0.881	0.911	(0.750, 1.107)
F11*	13.123	1.102	(1.046, 1.161)	F11*	8.036	1.111	(1.033, 1.194)
F12	0.905	0.971	(0.915, 1.031)	F12	0.437	0.973	(0.896, 1.056)
F13	2.723	1.103	(0.982, 1.240)	F13*	15.503	1.385	(1.178, 1.629)
F14*	13.148	1.104	(1.046, 1.164)	F14*	3.545	1.073	(0.997, 1.155)
F15	0.001	1.002	(0.913, 1.099)	F15	0.461	0.956	(0.841, 1.088)
F16	0.062	0.989	(0.906, 1.080)	F16	0.023	1.009	(0.894, 1.139)
F17*	17.680	1.171	(1.088, 1.261)	F17*	9.869	1.177	(1.063, 1.303)
Total ER (2-year pre-post-index date; *n*=3939)				**Total IH (2-year pre-post-index date; n=3939)**			
Omnibus	*AIC*	*BIC*	*-2LL*	*Omnibus*	*AIC*	*BIC*	*-2LL*
261.875***	22346.181	22459.197	-11155.090	95.725***	11835.319	11948.335	-5899.659
Poisson	*Wald*	*OR*	*95% CI OR*	*Poisson*	*Wald*	*OR*	*95% CI OR*
Intercept*	24.299	1.939	(1.490, 2.523)	Intercept*	7.735	0.592	(0.409, 0.857)
F1*	14.186	0.838	(0.765, 0.919)	F1*	3.996	0.878	(0.773, 0.997)
F2*	42.305	0.861	(0.823, 0.901)	F2	3.663	0.939	(0.881, 1.002)
F3*	7.308	0.963	(0.938, 0.990)	F3	0.007	0.998	(0.961, 1.037)
F4	0.278	1.018	(0.953, 1.088)	F4	0.472	1.033	(0.941, 1.134)
F5	0.385	0.949	(0.805, 1.119)	F5*	11.089	1.411	(1.152, 1.728)
F6*	7.885	0.885	(0.812, 1.119)	F6	1.832	0.921	(0.818, 1.038)
F7*	76.353	0.810	(0.772, 0.849)	F7	2.608	0.948	(0.889, 1.011)
F8*	8.391	1.069	(1.022, 1.118)	F8*	4.853	1.074	(1.008, 1.144)
F9*	18.967	1.031	(1.017, 1.045)	F9	0.498	1.007	(0.988, 1.027)
F10*	10.471	0.848	(0.767, 0.937)	F10	2.853	0.886	(0.770, 1.020)

F11*	8.469	1.056	(1.018, 1.096)	F11*	6.364	1.069	(1.015, 1.126)
F12	2.137	1.032	(0.989, 1.075)	F12	0.110	1.010	(0.952, 1.071)
F13	0.237	1.021	(0.940, 1.108)	F13*	7.825	1.179	(1.051, 1.323)
F14*	61.888	1.161	(1.119, 1.206)	F14*	9.584	1.086	(1.031, 1.145)
F15	1.063	0.966	(0.906, 1.031)	F15	0.791	0.959	(0.875, 1.051)
F16	1.860	1.044	(0.981, 1.111)	F16*	3.932	1.091	(1.001 1.189)
F17*	54.239	1.208	(1.149, 1.271)	F17*	41.275	1.251	(1.168, 1.339)

Notes: Factors with an "" are statistically significant at a p-value < 0.001.*

***Table 6*: Backward stepwise model fit & regression results of confirmed factors by any acute-care or unmet needs outcomes**

Unmet Needs 1 - Needed healthcare, Y = 1 (didn't receive it)			**Unmet Needs 2 – EH/MH/SUD help; Y = 1 (didn't receive it)**		
HCN1 (0=3007, 1=796)			*HCN2* (0=2953, 1=452)		
Model 1 Full GLM Binary Logistic Regression Model Fit Estimates by Outcome					
AIC	*BIC*	*-2LL*	*AIC*	*BIC*	*-2LL*
3138.17	3250.55	-1551.09	1989.369	2099.763	-976.684
Hosmer and Lemeshow Test					
	chi^2 (df)	*p-value*		*chi^2 (df)*	*p-value*
Step 1	19.265 (*8*)	0.014	Step 1	3.76 (*8*)	0.88
Omnibus Tests of Model Coefficients					
	chi^2 (df)	*p-value*		*chi^2 (df)*	*p-value*
Step 1	800.004 (*17*)	< 0.001	Step 1	713.247 (17)	< 0.001
Model 1	800.004 (*17*)	< 0.001	Model 1	713.247 (17)	< 0.001
Model 2 Parsimonious GLM Binary Logistic Regression Model Fit Estimates by Outcome					
AIC	BIC	-2LL	AIC	BIC	-2LL
3174.735	3249.808	-1575.367	2553.814	2611.088	-1267.907
Hosmer and Lemeshow Test					
	chi^2 (df)	*p-value*		*chi^2 (df)*	*p-value*

Step 7	17.648 (*8*)	0.024	Step 10	24.459 (*8*)	0.002

Omnibus Tests of Model Coefficients

	chi^2	*p-value*		*chi^2*	*p-value*
Step 7	-2.266 (*1*)	0.132	Step 10	-2.342 (*1*)	0.126
Model 7	794.195 (*11*)	< 0.001	Model 10	707.324 (*8*)	< 0.001

Any ER [dichotomous 2-year ER visit record generation; Y = 1 (at least 1 visit)]			**Any IH [dichotomous 2-year IH visit record generation; Y = 1 (at least 1 visit)]**		
AnyER (*0=2704, 1=1235*)			*AnyIH* (0=2819, 1=1120)		
Model 1 Full GLM Binary Logistic Regression Model Fit Estimates by Outcome					
AIC	*BIC*	*-2LL*	*AIC*	*BIC*	*-2LL*
4912.917	5025.933	-2438.458	4715.156	4828.173	-2339.578
Hosmer and Lemeshow Test					
	chi^2 (df)	*p-value*		*chi^2 (df)*	*p-value*
Step 1	5.223 (*8*)	0.734	Step 1	10.147 (*8*)	0.255
Omnibus Tests of Model Coefficients					
	chi^2 (df)	*p-value*		*chi^2 (df)*	*p-value*
Step 1	22.388 (*17*)	0.170	Step 1	24.026 (17)	0.119
Model 1	22.388 (*17*)	0.170	Model 1	24.026 (17)	0.119
Model 2 Parsimonious GLM Binary Logistic Regression Model Fit Estimates by Outcome					
AIC	BIC	-2LL	AIC	BIC	-2LL
482.529	503.413	-238.265	222.122	241.706	-108.061
Hosmer and Lemeshow Test					
	chi^2 (df)	*p-value*		*chi^2 (df)*	*p-value*
Step 16	4.415 (*8*)	0.818	Step 16	6.135 (5)	0.293

Omnibus Tests of Model Coefficients					
	chi^2	*p-value*		*chi^2*	*p-value*
Step 16	-1.807 (*1*)	0.132	Step 16	-2.579 (*1*)	0.108
Model 16	10.533 (2)	0.005	Model 16	12.897 (2)	< 0.002

Notes: Model fit: AIC, Akaike Information Criteria; BIC, Bayesian Information Criteria; -2LL, log-likelihood; chi^2 (df), chi^2 test statistic with degrees of freedom; Hosmer and Lemeshow Test non-significant value, good logistic regression model fit; Omnibus Tests of Model Coefficient, step significance means extra stepwise procedure was significant compared to previous step, model significance means the overall model was significant. Model number, final step for stepwise procedure.

***Table 7*: Parsimonious model using backward stepwise (likelihood ratio) elimination binary logistic regression, empirical variable selection strategy, with generalized linear modeling approach**

Outcomes	*HCN1* [*n=3851*(*47.8%*); *No=809*(21.0%); *Yes=3042*(79.0%)]					*HCN2* [*n=4289*(53.2%); *No=3712*(86.5%); *Yes=577*(13.5%)]				
Predictors	*M(SD)*	*Wald(df)*	*p-value*	*OR*	*95% CI OR*	*M(SD)*	*Wald(df)*	*p-value*	*OR*	*95% CI OR*
Intercept		225.049(1)	0	0.012	(0.007,0.022)		263.740(1)	0.000	0.007	(0.004, 0.012)
F1	0.149(0.310)	100.692(1)	0.000	3.701	(2.866, 4.779)	0.138(.298)	55.732(1)	<0.001	2.915	(2.201, 3.860)
F2	1.866(0.873)	3.799(1)	0.051	1.152	(0.999, 1.327)	1.907(0.861)	10.174(1)	0.001	1.260	(1.093, 1.453)
F3										
F4	1.135(0.513)	54.500(1)	<0.001	2.088	(1.717, 2.539)	1.141(0.514)	147.198(1)	0.000	4.176	(3.315, 5.261)
F5	0.035(0.163)	35.131(1)	<0.001	4.262	(2.639, 6.884)	0.036(0.165)	9.254(1)	0.002	2.082	(1.298, 3.339)
F6										
F7										
F8						1.748(0.873)	50.448(1)	<0.001	1.503	(1.304, 1.732)
F9	3.003(2.247)	91.020(1)	0.000	1.24	(1.186, 1.296)					
F10										
F11	1.163(1.128)	53.449(1)	<0.001	1.548	(1.377, 1.740)					
F12	1.241(1.205)	18.964(1)	<0.001	0.753	(0.663, 0.856)					
F13	0.978(0.343)	3.587(1)	0.058	0.786	(0.612, 1.008)					
F14	1.387(0.776)	18.480(1)	<0.001	1.319	(1.163, 1.497)	1.393(0.771)	31.600(1)	<0.001	2.005	(1.630, 2.466)
F15	1.199(0.439)	28.894(1)	<0.001	1.715	(1.409, 2.087)	1.204(0.469)	43.441(1)	<0.001	0.515	(0.429, 0.619)
F16	0.771(0.457)	6.975(1)	0.008	0.767	(0.630, 0.934)					
F17						0.162(0.411)	4.384(1)	0.036	1.240	(1.014, 1.518)
Outcomes	*AllER [n=7796(96.8%); No=5400(69.3%); Yes=2396(30.7%)]*					*AllIH [n=5055(62.7%); No=3627(71.8%); Yes=1428(28.2%)]*				
Predictors	*M(SD)*	*Wald(df)*	*p-value*	*OR*	*95% CI OR*	*M(SD)*	*Wald(df)*	*p-value*	*OR*	*95% CI OR*
Intercept		305.243(1)	0.000	0.411	(0.371, 0.454)		90.498(1)	0.000	0.441	(0.372, 0.522)
F1										
F2										
F3										
F4										
F5										
F6										

F7										
F8										
F9										
F10										
F11										
F12										
F13										
F14	1.374(0.772)	2.245(1)	0.134	1.049	(0.985, 1.117)					
F15						1.197(0.469)	2.780(1)	0.095	0.895	(0.785, 1.020)
F16										
F17	0.123(0.398)	2.529(1)	0.112	1.099	(0.978, 1.235)	0.169(0.423)	2.705(1)	0.100	1.124	(0.978, 1.291)

***Table 8*: Odds ratios heat zone map of HERO Care survey health factors and study outcomes**

Odds Ratios	**Base ER**	**Follow ER**	**Total ER**	Any ER	Base IH	Follow IH	**Total IH**	Any IH	**UN 1**	**UN 2**
TPN	0.816	0.861	0.838		0.879	0.874	0.878		3.730	3.003
HBS	0.856	0.867	0.861		0.958	0.922	0.939		1.162	1.221
SNI	0.984	0.942	0.963		0.997	0.999	0.998			
MDu	0.978	1.060	1.018		1.054	1.011	1.033		2.078	4.173
MI	0.924	0.972	0.949		1.563	1.261	1.411		4.226	2.336
FI	0.942	0.828	0.885		0.943	0.899	0.921			
ADL	0.778	0.843	0.810		0.953	0.944	0.948			
QoL	1.052	1.087	1.069		1.088	1.062	1.074			0.523
PE	1.036	1.025	1.031		1.028	0.987	1.007		1.242	
MDf	0.825	0.872	0.848		0.861	0.911	0.886			
HM	1.014	1.102	1.056		1.027	1.111	1.069		1.534	
IADL	1.093	0.971	1.032		1.050	0.973	1.010		0.767	
C-19:RHC	0.946	1.103	1.021		1.000	1.385	1.179		0.748	
IBT	1.220	1.104	1.161	1.049	1.100	1.073	1.086		1.338	1.435

C-19:EH	0.933	1.002	0.966		0.960	0.956	0.959	0.895	1.691	2.216
C-19:I	1.101	0.989	1.044		1.184	1.009	1.091		0.784	
SUD	1.243	1.171	1.208	1.099	1.324	1.177	1.251	1.124		1.376

Notes: Red, statistically significant association with larger adverse health factor relationship to outcome, implying a deleterious health factor-outcome relationship; Blue, statistically significant association with smaller adverse health factor relationship to outcome, implying a protective health factor-outcome relationship.

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VITA

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Manuscripts Under Review/Revision and Abstracts/Posters Accepted/Submitted for Presentation

Validating the Hospital Survey on Patient Safety Culture version 1 within a Latin American Context across 5 countries; Richard Munoz, Galed Hakin, Alejandro Arrieta; accepted ISQUA 2023 and Baptist Health Conference 2023, under review.

Validating the Hospital Survey on Patient Safety Culture version 2 within a Latin American Context, building and comparing a region-specific versus country-specific model(s); Richard Munoz, Alejandro Arrieta; postponed until version 1 above is published.

Associating Health Status Attributes to Acute-Care Usage in High-Need, High-Risk Veterans in Miami; Richard Munoz, subsequent authorship to be determined; to be incorporated as a dissertation paper, under review.

Arrieta A, Munoz R, Validation of the Hospital Survey on Patient Safety Culture in 5 Latin American Countries, The International Society for Quality in Health Care (ISQua). Abstract accepted for 15-minute oral presentation at ISQua's 39th International Conference in Seoul, Korea, Monday, August 28th, 2023.

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Dang S, Garcia S, Desir M, Munoz R, Noel P, Hansen J, Brintz BJ, Valenci W, Rupper R, Bouldin E, Trivedi R, Penney L, Pugh MJ, Kinosian B, Intrator O, Leykum L. Identifying Unmet Needs of High-Need, High-Risk Veterans and their Caregivers Using a Prospective Survey. Accepted for oral presentation: 2023 VA Health Services Research & Development/QUERI National Meeting, February 8-10, Baltimore Inner Harbor.

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98th percentile in Graduate Record Examinations Writing section
Hand-picked 1/6 from 100+ employees to explore internal retail theft; culprit found

"No matter what people tell you, words and ideas can change the world." – *Robin Williams*