Published in final edited form as:

Nurs Res. 2016 ; 65(6): 425–434. doi:10.1097/NNR.000000000000185.

Multiple Chronic Conditions and Hospitalizations Among Recipients of Long-Term Services and Supports

Janet H. Van Cleave, PhD, RN, AOCNP, ACNP-BC,

Assistant Professor, New York University, Rory Meyers College of Nursing, New York, NY

Brian L. Egleston, PhD,

Associate Research Professor, Biostatistics Facility, Fox Chase Cancer Center, Philadelphia, PA

Katherine M. Abbott, PhD, MGS,

Assistant Professor of Gerontology, Miami University, Oxford, OH

Karen B. Hirschman, PhD, MSW,

NewCourtland Term Chair in Health Transitions Research, Research Associate Professor of Nursing, University of Pennsylvania School of Nursing, Philadelphia, PA

Aditi Rao, PhD, RN, and

Director of Nursing Practice, Hospital of the University of Pennsylvania, Philadelphia, PA

Mary D. Naylor, PhD, RN, FAAN

Marian S. Ware Professor in Gerontology, Director, NewCourtland Center for Transitions and Health, University of Pennsylvania School of Nursing, Philadelphia, PA

Abstract

Background—Among older adults receiving long term-services and supports (LTSS), debilitating hospitalizations is a pervasive clinical and research problem. Multiple chronic conditions (MCC) are prevalent in LTSS recipients. However, the combination of MCC and diseases associated with hospitalizations of LTSS recipients is unclear.

Objective—The purpose of this analysis was to determine the association between classes of MCC in newly enrolled LTSS recipients and the number of hospitalizations over a one-year period following enrollment.

Methods—This report is based on secondary analysis of extant data from a longitudinal cohort study of 470 new recipients of LTSS, ages 60 years and older, receiving services in assisted living facilities, nursing homes, or through home- and community-based services. Using baseline chronic

Corresponding Author: Janet H. Van Cleave, PhD, RN, Assistant Professor, New York University, Rory Meyers College of Nursing, 433 First Avenue, 4th Floor, Room 408, New York, NY 10010 (janet.vancleave@nyu.edu).

Janet H. Van Cleave, PhD, RN, is Assistant Professor, New York University, Rory Meyers College of Nursing, New York, NY.

Brian L. Egleston, PhD, is Associate Research Professor, Biostatistics Facility, Fox Chase Cancer Center, Philadelphia, PA.

Katherine M. Abbott, PhD, MGS, is Assistant Professor of Gerontology, Miami University, Oxford, OH.

Karen B. Hirschman, PhD, MSW, is NewCourtland Term Chair in Health Transitions Research and Research Associate Professor of Nursing, University of Pennsylvania School of Nursing, Philadelphia, PA.

Aditi Rao, PhD, RN, is Director of Nursing Practice, Hospital of the University of Pennsylvania, Philadelphia, PA.

Mary D. Naylor, PhD, RN, FAAN is Marian S. Ware Professor in Gerontology, Director, NewCourtland Center for Transitions and Health, University of Pennsylvania School of Nursing, Philadelphia, PA.

The authors have no conflicts of interest to report.

conditions reported in medical records, latent class analysis (LCA) was used to identify classes of MCC and posterior probabilities of membership in each class. Poisson regressions were used to estimate the relative ratio between posterior probabilities of class membership and number of hospitalizations during the 3 month period prior to the start of LTSS (baseline) and then every three months forward through 12 months.

Results—Three latent MCC-based classes named Cardiopulmonary, Cerebrovascular/Paralysis, and All Other Conditions were identified. The Cardiopulmonary class was associated with elevated numbers of hospitalization compared to the All Other Conditions class (relative ratio [RR] = 1.88, 95% CI [1.33, 2.65], $p < .001$).

Conclusion—Older LTSS recipients with a combination of MCCs that includes cardiopulmonary conditions have increased risk for hospitalization.

Keywords

assisted living facilities; chronic illness; homemaker services; hospitalization; latent class analysis; nursing homes

Among older adults receiving long term services and supports (LTSS), preventing costly, debilitating hospitalizations is a pervasive clinical and research challenge (Castle & Mor, 1996; Grabowski, Stewart, Broderick, & Coots, 2008; Konetzka, Spector, & Limcangco, 2008; Wysocki et al., 2014). The population is frail, requires services to support daily activities, and has a high risk for hospitalization (Commission on Long-Term Care, 2013; O'Shaughnessy, 2014; Wysocki et al., 2014). For frail older adults receiving LTSS, hospitalizations have adverse consequences. Hospitalization of older adults is associated with negative health outcomes, such as falls and decline in activities of daily living (Boyd et al., 2008; Covinsky et al., 2003; Gillick, Serrell, & Gillick, 1982). Decline in activities of daily living during hospitalization is predictive of increased mortality up to one year after hospitalization (Boyd et al., 2008; Covinsky et al., 2003).

Older LTSS recipients live with multiple chronic conditions (MCC) that are often the cause of their disability, and lead to severe illness requiring hospitalization (DeJonge, Taler, & Boling, 2009). Moreover, MCCs in LTSS recipients increases the complexity of care management across settings and among care providers (Norris et al., 2008). However, combinations of MCCs in LTSS recipients that cause severe illness requiring hospitalizations are unclear.

Understanding the association between MCCs and hospitalization is growing in importance as the number of persons with MCCs is increasing. In the U.S., in 2000, 125 million persons had one or more chronic conditions (Anderson, 2010). By 2030, this number is expected to increase by more than 1% each year. Recognizing that MCCs are an important public health challenge, the U.S. Department of Health and Human Services created the Multiple Chronic Conditions (MCC) Interagency Workgroup to address the needs of people with MCC. One of the overarching goals of the framework is to generate research to bridge knowledge gaps about individuals with multiple chronic conditions (U.S. Department of Health and Human Services, 2010).

LTSS are provided for people with physical, cognitive, or mental disabilities to maintain their quality of living and independence (Commission on Long-Term Care, 2013; O'Shaughnessy, 2014). These services are wide ranging, varying from assistance with activities of daily living (ADLs)—such as bathing, dressing, eating, transferring, and walking—to instrumental activities of daily living (IADLs)—such as meal preparation, money management, and housekeeping. As indicated by the name, these services are provided over an extended period of time (Commission on Long-Term Care, 2013). Recipients of LTSS utilize services in a variety of settings—from home and community to institutional settings (Commission on Long-Term Care, 2013). In the U.S., LTSSs are provided to 12 million people (Commission on Long-Term Care, 2013). Although the population that requires these services ranges from children to older adults, 56% are age 65 and older (Commission on Long-Term Care, 2013). Projections of the U.S. population show that the demographic age group of 65 and older will grow substantially over the next two decades—from the current 47.8 million to 74.1 million by the year 2030—over 20% of the projected population (United State Census Bureau, 2015). If population trends continue as forecasted, the population needing LTSSs will increase substantially over the next several decades.

Older LTSS recipients live with MCCs that often are the cause of the need for LTSSs and decrease quality of life over time (Naylor et al., 2016). These chronic conditions include arthritis, heart conditions, diabetes, stroke, and dementia (Commission on Long-Term Care, 2013). For older LTSS recipients, these MCCs may lead to treatment interactions causing adverse outcomes, and may contribute to the complexity of nursing care across settings (Norris et al., 2008). MCCs can also cause severe illness, leading to costly and debilitating hospitalizations (DeJonge et al., 2009).

Several seminal studies have demonstrated the detrimental effects of hospitalization on older adults. In a study of 502 general medical patients, 40.5% of patients ages 70 and older experienced adverse effects, such as confusion, falling, and not eating, whereas only 8.8% of patients under age 70 had the same adverse effects (Gillick, Serrell, & Gillick, 1982). Further, those most advanced in age experience greater decline. For example, an analysis of patients enrolled in two randomized controlled studies to improve functional outcomes in adults ages 70 and older showed that patients age 80 and older had significantly greater odds of functional decline between admission and discharge (Covinsky et al., 2003). This functional decline during hospitalization may be associated with outcomes posthospitalization. In another analysis of older adults admitted to the hospital, researchers found 41.3% mortality rate among those discharged with a new or additional disability in self-care ADLs (Boyd et al., 2008).

Purpose and Approach

With the potential for a substantial growth of older adults requiring LTSS, it is especially important to build knowledge about the combinations of MCCs that may increase the risk of hospitalizations. This knowledge has the potential to lead to development of novel effective care management programs that can prevent hospitalizations. The purpose of this manuscript is to determine the MCCs associated with hospitalizations in LTSS recipients. The specific

aims of this analysis are to: (a) identify classes of MCC in new recipients of LTSS ages 60 and older; (b) determine demographic and clinical factors associated with the classes of MCC; and (c) determine associations between classes of MCCs and number of hospitalizations during the 3 month period prior to the start of LTSS (baseline) and then every three months forward through 12 months. Identifying the MCCs leading to hospitalizations in LTSS recipients holds potential to prevent hospitalizations and improve the quality of care received.

Methods

Design and Framework

A secondary data analysis was conducted using an extant data set from a National Institute on Aging-funded longitudinal observational cohort study entitled, *Health Related Quality of Life: Elders in Long Term Care (HRQoL), R01AG025524*, hereafter referred to as the “parent study” (Naylor et al., 2016; Zubritsky et al., 2013).

The vulnerability/risk/human response care (VRHR) framework (Shaver, 1985) guided the selection of the variables for the secondary data analysis. The VRHR framework is an ecological model of a biopsychosocial view of human health. This model posits that human health is the result of the interaction between an individual and the environment. As such, the goal of nursing care is to restore, maintain, or promote health (Shaver, 1985). For this study, the demographic, depressive symptoms, number of symptoms, function, and comorbidity variables represent the individual factors. The environment factors are represented by site of care and insurance variables. This study was approved by the New York University Langone Medical Center Institutional Review Board.

Overview of Parent Study

The parent study was reviewed and approved by the University of Pennsylvania Institutional Review Board. The purpose of the parent study was to investigate changes in multiple domains of health-related quality of life among older adults newly enrolled in LTSS, and receiving services in nursing homes (NH), assisted living facilities (ALF), and home- and community-based settings (HCBS). The study was conducted between 2007 and 2012 in the northeastern U.S. A convenience sample of 59 sites from 11 organizations in three states (Pennsylvania, New Jersey, and New York) participated in the study. Of the 59 participating sites, nine were freestanding NHs and 16 were part of continuing care retirement communities. The ALF sites were part of four large national chains, each with several facilities, within a 50-mile radius of Philadelphia (13 sites were freestanding and 16 sites were part of continuing care retirement communities). Five HCBS sites in Pennsylvania and New York states also participated in the parent study.

Procedures

For the parent study, data were collected using face-to-face interviews and medical record extractions. Research Associates (RA) were trained in collecting and recording data onto scan forms created in Verity TeleForm. These forms were processed into SPSS data files. All data were verified for accuracy and quality by the parent study team. Participants’ chronic

conditions were extracted from LTSS medical records or agency records by RAs. The research team experienced difficulty differentiating among chronic conditions that were active at baseline from those that were historical. All conditions, therefore, were considered present at the time of study enrollment. Chronic conditions were underreported for study participants receiving HCBS care from the visiting nurse service due to limited recording space in the agency's standard assessment forms. As a result, a query was sent to primary care clinicians or practices, and the researchers obtained an 80% response rate. Chronic condition data were converted to International Classification of Diseases, Tenth Revision (ICD-10) codes in preparation for the statistical analysis. Two members of the research team (JHV and AR), with either ICD-10 training or coding experience, reviewed each condition, and assigned codes based on definitions from the ICD-10 website and other extracted data from medical/agency records. To ensure reliability and consistency of their decisions, the researchers maintained rigorous documentation of decisions and assumptions. From this process, the researchers identified 579 chronic conditions in the dataset. After coding verification, the data were uploaded into STATA 12.0 (StataCorp, College Station, TX) for statistical analysis.

Study Sample

The parent study inclusion/exclusion criteria were designed to enroll a study population of older adults receiving LTSS who could participate in interviews. The inclusion criteria for the parent study were ages 60 and older, enrolled in LTSS within the preceding 60 days, ability to communicate verbally in English or Spanish, and score of 12 or greater on the Mini Mental State Examination (MMSE; Folstein, Folstein, & McHugh, 1975). The exclusion criteria were documentation in the medical record of expected discharge from LTSS, prior LTSS use, or terminal illness (e.g., prognosis < 6 months to live or enrolled in hospice care). All Institutional Review Boards approved the use of the MMSE as an assessment of study candidates' capacity to provide informed consent for participation. MMSE scores were adjusted for both age and education. Older adults who scored 23 on the MMSE provided written informed consent. Those who scored between 12 and 22 provided assent, and the legally authorized representative provided informed consent. The parent study enrolled 470 participants. The study findings demonstrated that quality of life ratings decreased over time. Quality of life was highest among participants who received LTSS from ALFs, followed by NHs, then HCBS (Naylor et al., 2016). All participants in the parent study were included in the secondary data analysis reported in this manuscript.

Measures

Key independent variable: Probability of MCC class membership—The main independent variable for this analysis was the posterior probability of membership in a class of MCCs at study enrollment. Probabilities were estimated as part of the LCA procedure (Skrondal & Rabe-Hesketh, 2004, pp. 74–75, 288–292). A latent class is defined as a subpopulation of individuals; in this case, the subpopulation was defined by co-existing conditions within an individual with or without a causal link (van den Akker, Buntinx, Metsemakers, Roos, & Knottnerus, 1998; Yancik et al., 2007). As the number of potential combinations of MCCs based on disease codes is huge (Sorace et al., 2011), the chronic conditions selected for the LCA were based on the Charlson Comorbidity Index (CCI), an

accepted comorbidity risk score designed to predict mortality that has also been used as a general summary measure of the overall burden of comorbidities (Austin, Wong, Uzzo, Beck, & Egleston, 2015; Egleston, Uzzo, Beck, & Wong, 2015). These chronic condition categories were: AIDS/HIV; cerebrovascular disease; congestive heart failure; chronic pulmonary disease; dementia; diabetes without chronic complications; diabetes with chronic complications; hemiplegia or paraplegia; mild, moderate, or severe liver disease; any malignancy, including leukemia and lymphoma, metastasis, or solid tumor; myocardial infarction; peripheral vascular disease; peptic ulcer disease; rheumatologic disease; and renal diseases. For the analysis, ICD10 codes used to represent these categories were based on the algorithm reported by Sundararajan et al. (2004).

Covariates—Demographic data of age, race, education, insurance (Medicaid, Medicare Part A, Medicare Parts A and B), and site of LTSS (NH, ALF, and HCBS) were included in the analysis as covariates. Depressive symptomatology was also a covariate. The Geriatric Depression Scale Short Form (GDS-SF) was used to assess the presence and severity of depression. GDS-SF scores have demonstrated validity and reliability for measuring depression among both impaired and cognitively intact older adults. Higher scores indicate greater depressive symptoms (Yesavage et al., 1983). The number of symptoms was measured using the Symptom Bothersome Scale, which includes a list of 13 physical symptoms typically associated with aging or chronic illness (e.g., aching, pain, stiffness, fatigue). Participants rated the degree to which they are bothered by each symptom on a 0 to 3 scale (0 = *not present*; 1 = *present not bothered*; 2 = *bothered a little*; and 3 = *bothered a great deal*). Symptoms were coded as absent (Symptom = 0) when participants rated items 0 or 1, and present (Symptom = 1) when participants rated items 2 or 3. Recoded symptom responses were summed, with higher total scores indicating presence of greater number of symptoms. Scores on the scale have demonstrated validity, using the known groups approach, by identifying respondents with worse functional status. Reliability estimated using Cronbach's alpha was 0.78 to 0.85 (Heidrich, 1993). Functional status was measured using the Katz Index of Activities of Daily Living (KADL). Participant self-reports or staff member proxy reports for those with mild to moderate cognitive impairment (defined as MMSE scores 12 – 23) were used. The six-item KADL assesses deficits in bathing, dressing, toileting, transferring, continence, and feeding. Scores range from 0–6, with higher scores indicating more deficits in function (Katz, 1983).

Outcome: Number of Hospitalizations—The main outcome variable for this study was the number of hospitalizations beginning at the 3 month period prior to the start of LTSS (baseline) and then every three months forward through 12 months. Data regarding hospitalizations were extracted from the LTSS medical records at baseline, 3-, 6-, 9-, and 12-months postenrollment, and recorded on the Chart Abstraction Tool used in the parent study. The use of the data from the 3-month data collection periods lessened bias resulting from death, since individuals were less likely to die in each 3 month intervals than in longer intervals, such as one year. Time of data collection was included in the analysis as a covariate to detect temporal trends.

Charlson Comorbidity Index—We compared the performance of the LCA to the performance of the CCI (Charlson, Pompei, Ales, & MacKenzie, 1987). We selected the CCI because it is a widely cited, accepted comorbidity risk score designed to predict mortality. According to the Web of Science, the CCI has been cited over 14,000 times. It has also been used as a general summary measure of the overall burden of comorbidities (Austin et al., 2015; Egleston et al., 2015). The CCI is a weighted index that accounts for the number and the seriousness of comorbid disease. The weights represent the hazard ratio (HR) of mortality for conditions that had a significant impact on mortality. For example, conditions that had $HR > 1.2$ but < 1.5 were assigned a weight of 1; conditions with HR of > 1.5 but < 2.5 were assigned a weight of 2, and so on. A weight of six represents the most severe condition (Charlson, Pompei, Ales, & MacKenzie, 1987).

Statistical Analysis

The statistical analysis was completed in three steps. First, LCA was conducted to identify latent subpopulations based on MCCs and estimate posterior probabilities of membership in each class. Next, *t*-tests and ANOVA were used to evaluate differences in participant characteristics across the classes using highest posterior probabilities of class membership. Third, Poisson regression analyses were conducted to investigate the association between the posterior probabilities of class membership and number of hospitalizations per three-month period, using a population average model.

Latent class analysis—LCA (Skron dal & Rabe-Hesketh, 2004) was used to identify subpopulations (i.e., latent classes) of MCC that likely occurred together within individuals (i.e., classes of chronic conditions). As part of the LCA, probability of having a disease within each class (*yes* or *no* to having a disease) is estimated. The model was also used to estimate the proportion of the population that belongs to each class. For LCA, STATA 12.0 (StataCorp, College Station, TX) and the gllamm macro were used for analyses.

A series of models with 1, 2, 3, and 4 latent classes were estimated. A likelihood ratio test assessed whether increasing the number of model classes improved the fit of the statistical model with the observed data. Statistical significance was set at $p < .05$. The minimum Akaike Information Criterion (AIC) was also considered in the model selection process.

An assumption of the LCA is that study participants belong to one of the estimated classes (subpopulations), although the exact class is unknown. Based on this assumption, LCA provides the posterior probability of class membership (estimate of each participant's probability of belonging to each class). We assigned study participants to classes based on their maximum posterior probability, and then characterized the classes using descriptive statistics.

Poisson regression analysis—Poisson regression analysis was used to investigate the association between the posterior probabilities of MCC class membership and number of hospitalizations in a three-month period, using a population average model. Generalized estimating equations, were used to account for longitudinal data (Diggle, Heagerty, Liang, & Zeger, 2013). The exchangeable correlation matrix was used to model the repeated measures data. Twenty nine participants (6%) were excluded from the analysis due to missing data.

Covariates were demographics, time of data collection, depressive symptoms, number of symptoms, functional status, and LTSS residence sites. The exponentiated coefficients of the Poisson regression equations were used to estimate relative percentage differences (i.e., relative ratios [RR]) in hospitalizations for one-unit difference in the covariates. With respect to latent classes, regression coefficients indexed the relative percent increase (i.e., RR) in number of hospitalizations for posterior probabilities approaching 1 compared to those approaching 0. One class was designated as the reference class against which differences were compared.

The use of the LCA is a novel approach to representing disease burden. Therefore, the performance of the LCA was compared to the performance of the CCI (Charlson, Pompei, Ales, & MacKenzie, 1987) using Poisson regression analysis. For this comparison, two additional Poisson regression analyses were conducted. The first Poisson regression included the CCI alone as the chronic condition risk score. The second Poisson regression included both the LCA posterior probabilities of class membership and CCI scores to assess findings using the LCA.

Results

Participant Characteristics

The majority of study participants were ages 80 or greater, female, and White (Table 1). The most prevalent condition among study participants was essential (primary) hypertension, unspecified ($n = 376$; 80%); followed by unspecified depressive episode ($n = 157$; 33%); and arthritis, unspecified ($n = 148$; 31%). Mortality was 11.3% (53/470) during the 12-month study period.

Latent Class Analysis

The likelihood ratio test indicated that the three-class model fit the data better than the two-class model, and had a similar fit to the four-class model (Table 2). Also, AIC was lowest for the three-class solution. Due to its conceptual clarity and statistical significance ($p < .0001$), a three-class model was selected.

The three classes included two that represented distinct types of MCCs, labeled Cardiopulmonary class and Cerebrovascular/Paralysis class. The third class consisted of a subpopulation without any particularly defining chronic conditions, and was labeled All Other Conditions class (See Table 3). The Cardiopulmonary class was primarily composed of individuals with a high prevalence of cardiac and pulmonary conditions. The most prevalent condition was congestive heart failure, which was present in 92% of the Cardiopulmonary class members. Other prevalent chronic conditions in the Cardiopulmonary class were myocardial infarction (54%), and pulmonary disease (41%). The Cerebrovascular Disease/Paralysis class was dominated by the prevalence of cerebrovascular disease (71%) and paralysis (27%) among class members. The All Other Conditions class was notable for a lower prevalence of MCC than either of the other two classes. The All Other Conditions class consisted primarily of women ages 80 and over receiving care in either ALF or HCBS (Table 4). Using highest posterior probability for each

participant, individuals had the greatest probability (66%) of membership in the All Other Conditions class, followed by Cardiopulmonary class (18%) and Cerebrovascular/Paralysis class (16%).

Study participants were assigned to one of the three latent classes based on maximum posterior probabilities (Table 4). Participant characteristics were different among the three latent classes. Those assigned to the Cardiopulmonary and Cerebrovascular Disease/Paralysis classes were younger than those in the All Other Conditions class. Those in the Cardiopulmonary and Cerebrovascular Disease/Paralysis classes were more likely to be male, Black/Other race, and reside in a nursing home. Medicaid patients were overrepresented in the Cardiopulmonary class compared to the Cerebrovascular Disease/Paralysis class or the All Other Conditions class.

Poisson Regression Analysis

Results from the Poisson regression analysis using a population average model showed a significant positive relationship between membership in the Cardiopulmonary class and number of hospitalizations (Table 5, Model 1) compared to the All Other Conditions class ($RR = 1.88$, 95% CI [1.33, 2.65], $p < .001$). Covariates with significant relationships with hospitalizations were greater depressive symptoms ($RR = 1.04$, 95% CI [1.01, 1.08], $p < .05$) and residence in nursing homes compared to assisted living facilities ($RR = 1.56$, 95% CI [1.04, 2.35], $p < .05$).

The relationship between posterior probabilities of class membership and number of hospitalizations, based on the population average model, is shown in Figure 1. Using restricted cubic splines as a smoothing function to generate Figure 1, we demonstrate that a participant approaching 1.0 probability (100%) of membership in the Cardiopulmonary Class averaged approximately 2.2 number of hospitalizations per year, whereas an individual approaching 0 probability (0%) of membership in the Cardiopulmonary Class averaged 0.8 hospitalizations per year. The decrease/increase in hospitalizations for the All Other Conditions class could be due to noisy variability in hospital data. A higher average number of hospitalizations represented greater individual risk for hospitalizations.

To compare the use of LCA and CCI scores in representing comorbidity disease burden, the Poisson regression analysis using only LCA found results that were similar to the Poisson regression using only CCI scores (Table 5, Models 1 and 2). As Model 2 demonstrates, CCI scores were associated with increased number of hospitalizations over a three-month period ($RR = 1.10$, 95% CI [1.02, 1.18], $p < .05$). The Poisson regression analysis using both the LCA and the CCI scores found that the Cardiopulmonary class estimates became statistically insignificant (Table 5, Model 3). In Model 3, the magnitude of the RR s for the latent class effects were modestly decreased while the magnitude of the RR for the CCI score became statistically insignificant (Cardiopulmonary class: $RR = 1.74$, 95% CI [0.98, 3.06], $p = .06$; CCI scores: $RR = 1.02$, 95% CI [0.91, 1.14], $p = .72$). The findings from this analysis support the findings of the LCA analysis.

Discussion

Among older adults receiving LTSS, the MCC class with high prevalence of specific cardiopulmonary chronic conditions impacted health in a manner associated with increased use of hospitalization. These findings underscore the growing need for developing healthcare management strategies to address MCCs—especially for chronically ill, older adults with cardiopulmonary conditions. Specifically for LTSS recipients, effective case management strategies have the potential to prevent hospitalizations by focusing on health problems arising from multiple cardiopulmonary conditions (DeJonge, Taler, & Boling, 2009; Wysocki et al., 2014).

Until recently, health services have emphasized a single disease approach. Unintended consequences have included polypharmacy and care provided by multiple providers (Anderson, 2010; Fried, Niehoff, Tjia, Redeker, & Goldstein, 2016). More recently, new health policies have been implemented to incentivize providers to address multiple chronic conditions. These strategies include provider reimbursement by Medicare for care coordination for MCC (Bautista, Covinsky, & Aronson, 2015). Although implementation of these new policies represents progress in developing case management strategies to address MCC, more research is needed. Some strategies that are proposed and need to be further explored include team approaches to prevention and management of polypharmacy, careful deliberation in expanding clinical practice guidelines to encompass MCC, and incorporating transitional care from hospital to residence within services provided by medical homes (Fried et al., 2016; Hirschman et al., 2015; Wilson et al., 2016).

Another key study finding is the difference in demographic characteristics among the three latent classes. Members of the classes with the greatest disease burden—Cardiopulmonary and Cerebrovascular Disease/Paralysis—were younger and resided in nursing homes. Individuals in these classes were also more likely to be Black than those in the All Other Conditions class. Racial disparities in LTSS are well documented. Older Blacks and Hispanics have higher rates of functional impairment (Commission on Long-Term Care, 2013). Whites have traditionally had greater use of NHs; however, utilization of NHs by Whites is declining, and the use of nursing homes by Black patients is rising (Commission on Long-Term Care, 2013). Our results reflect the current situation. Classes were also distinguished by insurance status, with those with greater disease burden more likely to be insured by Medicaid, perhaps reflecting an association between lower socioeconomic status and greater number of chronic conditions.

Our study adds to the literature by demonstrating the use of the LCA to identify subpopulations for potential disease management interventions. Although complex and focused on the population as a whole, these statistical analyses may be useful in developing personalized interventions. The LCA modeling technique could serve as an important analytical approach for a learning healthcare system that combines research strategies and clinical care (Institute of Medicine, 2013). In a learning healthcare system, LCA could be embedded within electronic health record or agency data systems to generate classes of MCC and individual probabilities of class membership that reflect local caseloads. Accordingly, clinicians could receive alerts in the electronic health records when individual

LTSS recipients have a high probability of membership in a class at increased risk for hospitalizations. After determining that interventions are clinically appropriate, providers could initiate evidence-based interventions that are individually tailored to prevent unnecessary hospitalizations. Ongoing analyses could update the individual probabilities of membership in classes of MCC at increased risk for hospitalizations. These analyses would provide information to indicate whether the interventions are increasing or decreasing the risk for hospitalizations. In this manner, the LCA could be used to efficiently match resources with needs and desires of patients. However, further work is needed at local, national, and international levels to realize the promise of using modeling techniques, such as the LCA, in the LTSS setting.

Our experience underscores the need for coordination and communication of information across the many settings that comprise LTSS. Some national healthcare systems are at the forefront of this technology, with the use of public registries and information technology at all levels of the health systems, while other national healthcare systems have yet to implement integrated information technology (Mossialos, Wenzl, Osborn, & Anderson, 2015). To promote a LTSS system that achieves improved care, improves health, and decreases cost, researchers, clinicians, and patients must move forward together to ensure data quality that informs a patient-centered learning healthcare system (Berwick, Nolan, & Whittington, 2008; Institute of Medicine, 2013).

Limitations

Some limitations decrease generalizability of the findings. First, the quality of medical records and agency data prevented the study team from distinguishing conditions that were historical from those that were active at study enrollment. Consequently, all conditions were considered present at time of data collection. This has significance for determining patterns of co-occurrence, including chronic conditions that independently co-exist from those that synergistically interact to cause adverse outcomes (Meghani et al., 2013; Norris et al., 2008).

Another limitation is that the inclusion and exclusion criteria of the parent study focused recruitment of LTSS recipients on those who had the ability to communicate verbally in English or Spanish and were not cognitively impaired. Exclusion of those with severe cognitive impairment may have contributed to underestimation of the association between cognitive disorders and hospitalizations.

Conclusion

Older LTSS recipients with MCCs with high prevalence of cardiopulmonary conditions are at risk for potentially debilitating and costly hospitalizations. New approaches in care management are needed to effectively manage multiple chronic conditions, and efficiently address needs and desires of individuals during vulnerable times that limit capacity for self-care.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

The authors acknowledge the following funding sources: *Health Related Quality of Life: Elders in Long Term Care, R01AG025524*, National Institute on Aging and National Institute of Nursing Research, Mary D. Naylor, Principal Investigator; *Individualized Care for At-Risk Older Adults, T32-NR009356*, National Institute of Nursing Research, Postdoctoral Research Fellowship; University of Pennsylvania, NewCourtland Center for Transitions and Health (Pilot Study), *Comorbidity Patterns of Elders with Cancer Receiving Long Term Services and Supports*, Janet H. Van Cleave, Principal Investigator.

The authors also acknowledge that parts of this manuscript were presented as a poster presentation at AcademyHealth Annual Research Meeting, Orlando, FL, June, 2012, and a podium presentation at the Gerontological Society of America 65th Annual Scientific Meeting, San Diego, CA, November, 2012. Citations to other papers based on this dataset are available as Supplemental Digital Content 1.

References

- Anderson, G. Chronic care: Making the case for ongoing care. Princeton, NJ: Robert Wood Johnson Foundation; 2010.
- Austin SR, Wong YN, Uzzo RG, Beck JR, Egleston BL. Why summary comorbidity measures such as the Charlson Comorbidity Index and Elixhauser Score Work. *Medical Care*. 2015; 53:e65–e72. DOI: 10.1097/MLR.0b013e318297429c [PubMed: 23703645]
- Bautista CA, Covinsky K, Aronson L. Chronic care management for Medicare patients—Reply. *JAMA*. 2015; 313:2286–2287. DOI: 10.1001/jama.2015.4984
- Berwick DM, Nolan TW, Whittington J. The triple aim: Care, health, and cost. *Health Affairs*. 2008; 27:759–769. DOI: 10.1377/hlthaff.27.3.759 [PubMed: 18474969]
- Boyd CM, Landefeld CS, Counsell SR, Palmer RM, Fortinsky RH, Kresevic D, ... Covinsky KE. Recovery of activities of daily living in older adults after hospitalization for acute medical illness. *Journal of the American Geriatrics Society*. 2008; 56:2171–2179. DOI: 10.1111/j.1532-5415.2008.02023.x [PubMed: 19093915]
- Castle NG, Mor V. Hospitalization of nursing home residents: A review of the literature, 1980–1995. *Medical Care Research and Review*. 1996; 53:123–148. [PubMed: 10157708]
- Charlson ME, Pompei P, Ales KL, MacKenzie CR. A new method of classifying prognostic comorbidity in longitudinal studies: Development and validation. *Journal of Chronic Diseases*. 1987; 40:373–383. DOI: 10.1016/0021-9681(87)90171-8 [PubMed: 3558716]
- Commission on Long-Term Care. Report to the Congress. Washington, DC: U.S. Senate Commission on Long-Term Care; 2013. Retrieved from <http://ltccommission.org/ltccommission/wp-content/uploads/2013/12/Commission-on-Long-Term-Care-Final-Report-9-26-13.pdf>
- Institute of Medicine. Best care at lower cost: The path to continuously learning health care in America. Washington, D.C: National Academies Press; 2013.
- Covinsky KE, Palmer RM, Fortinsky RH, Counsell SR, Stewart AL, Kresevic D, ... Landefeld CS. Loss of independence in activities of daily living in older adults hospitalized with medical illnesses: Increased vulnerability with age. *Journal of the American Geriatrics Society*. 2003; 51:451–458. DOI: 10.1046/j.1532-5415.2003.51152.x [PubMed: 12657063]
- DeJonge KE, Taler G, Boling PA. Independence at home: Community-based care for older adults with severe chronic illness. *Clinics in Geriatric Medicine*. 2009; 25:155–169. DOI: 10.1016/j.cger.2008.11.004 [PubMed: 19217500]
- Diggle, P.J.; Heagerty, P.; Liang, K-Y.; Zeger, S.L. Analysis of longitudinal data. 2. Oxford, UK: Oxford University Press; 2013.
- Egleston BL, Uzzo RG, Beck JR, Wong YN. A simple method for evaluating within sample prognostic balance achieved by published comorbidity summary measures. *Health Services Research*. 2015; 50:1179–1194. DOI: 10.1111/1475-6773.12276 [PubMed: 25523400]
- Folstein MF, Folstein SE, McHugh PR. “Mini-mental state.” A practical method for grading the cognitive state of patients for the clinician. *Journal of Psychiatric Research*. 1975; 12:189–198. [PubMed: 1202204]

- Fried TR, Niehoff K, Tija J, Redeker N, Goldstein MK. A Delphi process to address medication appropriateness for older persons with multiple chronic conditions. *BMC Geriatrics*. 2016; 16:1.doi: 10.1186/s12877-016-0240-3 [PubMed: 26729190]
- Gillick MR, Serrell NA, Gillick LS. Adverse consequences of hospitalization in the elderly. *Social Science & Medicine*. 1982; 16:1033–1038. DOI: 10.1016/0277-9536(82)90175-7 [PubMed: 6955965]
- Grabowski DC, Stewart KA, Broderick SM, Coots LA. Predictors of nursing home hospitalization: A review of the literature. *Medical Care Research and Review*. 2008; 65:3–39. DOI: 10.1177/1077558707308754 [PubMed: 18184869]
- Heidrich SM. The relationship between physical health and psychological well-being in elderly women: A developmental perspective. *Research in Nursing & Health*. 1993; 16:123–130. DOI: 10.1002/nur.4770160207 [PubMed: 8502764]
- Hirschman KB, Shaid E, Bixby MB, Badolato DJ, Barg R, Byrnes MB, ... Naylor MD. Transitional care in the patient-centered medical home: Lessons in adaptation. *Journal for Healthcare Quality*. 2015; doi: 10.1097/01.JHQ.0000462685.78253.e8
- Katz S. Assessing self-maintenance: Activities of daily living, mobility, and instrumental activities of daily living. *Journal of the American Geriatrics Society*. 1983; 31:721–727. DOI: 10.1111/j.1532-5415.1983.tb03391.x [PubMed: 6418786]
- Konetzka RT, Spector W, Limcangco MR. Reducing hospitalizations from long-term care settings. *Medical Care Research and Review*. 2008; 65:40–66. doi:1077558707307569. [PubMed: 17895516]
- Meghani SH, Buck HG, Dickson VV, Hammer MJ, Rabelo-Silva ER, Clark R, Naylor MD. The conceptualization and measurement of comorbidity: A review of the interprofessional discourse. *Nursing Research and Practice*. 2013; 2013:192782.doi: 10.1155/2013/192782 [PubMed: 24187618]
- Mossialos, E.; Wenzl, M.; Osborn, R.; Anderson, C., editors. *International profiles of health care systems*, 2014. New York, NY: The Commonwealth Fund; 2015.
- Naylor MD, Hirschman KB, Hanlon AL, Abbott KM, Bowles KH, Foust J, ... Zubritsky C. Factors associated with changes in perceived quality of life among elderly recipients of long-term services and supports. *Journal of the American Medical Directors Association*. 2016; 17:44–52. DOI: 10.1016/j.jamda.2015.07.019 [PubMed: 26412018]
- Norris SL, High K, Gill TM, Hennessy S, Kutner JS, Reuben DB, ... Landefeld CS. Health care for older Americans with multiple chronic conditions: A research agenda. *Journal of the American Geriatrics Society*. 2008; 56:149–159. DOI: 10.1111/j.1532-5415.2007.01530.x [PubMed: 18047493]
- O'Shaughnessy, CV. *National spending for long-term services and supports (LTSS)*, 2012. Washington, DC: National Health Policy Forum; 2014.
- Shaver JF. A biopsychosocial view of human health. *Nursing Outlook*. 1985; 33:186–191. [PubMed: 3848821]
- Skrondal, A.; Rabe-Hesketh, S., editors. *Generalized latent variable modeling: Multilevel, longitudinal, and structural equation models*. Boca Raton, FL: CRC Press; 2004.
- Sorace J, Wong HH, Worrall C, Kelman J, Saneinejad S, MaCurdy T. The complexity of disease combinations in the Medicare population. *Population Health Management*. 2011; 14:161–166. DOI: 10.1089/pop.2010.0044 [PubMed: 21241184]
- Sundararajan V, Henderson T, Perry C, Muggivan A, Quan H, Ghali WA. New ICD-10 version of the Charlson comorbidity index predicted in-hospital mortality. *Journal of Clinical Epidemiology*. 2004; 57:1288–1294. DOI: 10.1016/j.jclinepi.2004.03.012 [PubMed: 15617955]
- United States Census Bureau. *Population projections: Table 3. Projections of the population by sex and selected age groups for the United States: 2015 to 2060*. 2015. Retrieved from <http://www.census.gov/population/projections/data/national/2014/summarytables.html>
- U.S. Department of Health and Human Services. *Multiple chronic conditions: A strategic framework—Optimum health and quality of life for individuals with multiple chronic conditions*. 2010. Retrieved from http://www.hhs.gov/ash/initiatives/mcc/mcc_framework.pdf

- van den Akker M, Buntinx F, Metsemakers JFM, Roos S, Knottnerus JA. Multimorbidity in general practice: Prevalence, incidence, and determinants of co-occurring chronic and recurrent diseases. *Journal of Clinical Epidemiology*. 1998; 51:367–375. S0895-4356(97)00306-5. [PubMed: 9619963]
- Wilson KC, Gould MK, Krishnan JA, Boyd CM, Brozek JL, Cooke CR. ... ATS Guideline Methodology Working Group. An official American Thoracic Society Workshop report. A framework for addressing multimorbidity in clinical practice guidelines for pulmonary disease, critical illness, and sleep disorders. *Annals of the American Thoracic Society*. 2016; 13(Suppl 3):S12–S21. DOI: 10.1513/AnnalsATS.201601-007ST [PubMed: 26963362]
- Wysocki A, Kane RL, Golberstein E, Dowd B, Lum T, Shippee T. The association between long-term care setting and potentially preventable hospitalizations among older dual eligibles. *Health Services Research*. 2014; 49:778–797. DOI: 10.1111/1475-6773.12168 [PubMed: 24628471]
- Yancik R, Ershler W, Satariano W, Hazzard W, Cohen HJ, Ferrucci L. Report of the national institute on aging task force on comorbidity. *Journals of Gerontology Series A: Biological Sciences and Medical Sciences*. 2007; 62:275–280. <http://biomedgerontology.oxfordjournals.org/content/62/3/275.full.pdf+html>.
- Yesavage JA, Brink TL, Rose TL, Lum O, Huang V, Adey M, Leirer VO. Development and validation of a geriatric depression screening scale: A preliminary report. *Journal of Psychiatric Research*. 1983; 17:37–49. DOI: 10.1016/0022-3956(82)90033-4
- Zubritsky C, Abbott KM, Hirschman KB, Bowles KH, Foust JB, Naylor MD. Health-related quality of life: Expanding a conceptual framework to include older adults who receive long-term services and supports. *Gerontologist*. 2013; 53:205–210. DOI: 10.1093/geront/gns093 [PubMed: 22859435]

FIGURE 1.

Using restricted cubic splines with linear regression provides a graphical display of the relationship between estimated probabilities of class membership and population average number of hospitalizations over 3-month period. For example, a participant with a probability of membership in the Cardiopulmonary Class approaching 1.0 (100%) averaged 0.55 hospitalizations per quarter, which translates to approximately 2.2 hospitalizations per year ($0.55/\text{quarter} \times 4 = 2.2/\text{year}$). In contrast, an individual with a probability of membership in the Cardiopulmonary Class approaching 0 (0%) averaged approximately 0.2 hospitalizations per quarter, which translates to 0.8 hospitalizations per year ($0.2/\text{quarter} \times 4 = 0.8/\text{year}$).

TABLE 1

Participant Characteristics

Characteristic	<i>n</i>	(%)
Age (years)		
60–69	59	(12.6)
70–74	60	(12.8)
75–79	68	(14.5)
80–84	88	(18.7)
85	195	(41.5)
Gender (female)	334	(71.1)
Race		
White	239	(50.9)
Black ^a	228	(48.5)
Missing	3	(0.6)
Ethnicity (Non-Hispanic)	377	(80.2)
Marital status		
Single	51	(10.9)
Married	93	(19.8)
Widowed	243	(51.7)
Divorced or separated	82	(17.4)
Education		
<HS	97	(20.6)
HS	187	(39.8)
>HS	185	(39.4)
LTSS (type)		
Assisted living facility	156	(33.2)
Nursing home	158	(33.6)
HCBS	156	(33.2)
Income (annual) (\$)		
0–9,999	130	(27.7)
10,000–19,999	87	(18.5)
20,000–39,999	40	(8.5)
40,000	59	(12.6)
Unknown	154	(32.8)
	<i>M</i>	(<i>SD</i>)
GDS–SF ^b	4.55	(3.39)
Comorbidities (number)	10	(4.41)

Note. *N* = 470. GDS-SF = Geriatric Depression Scale–Short Form; HCBS = home or community-based setting; HS = high school; LTSS = long-term services and supports.

^aIncludes African American or Other Non-White.

^b Higher scores indicate worse depressive symptoms.

Author Manuscript

Author Manuscript

Author Manuscript

Author Manuscript

TABLE 2

LCA Model Selection Summary

Criterion	Number of classes			
	1	2	3	4
LL	-2636.1	-2596.6	-2574.9	-2565.1
AIC	5296.2	5241.2	5221.8	5226.2
LR		79.0	43.4	19.6
<i>p</i>		<.0001	<.0001	.04

Note. *N* = 470. AIC = Akaike Information Criterion; LCA = latent class analysis; LL = log likelihood. LR = likelihood ratio. The difference in degrees of freedom between models was 12.

TABLE 3

Chronic Conditions Within Classes

Condition	Cardiopulmonary	Cerebrovascular ^a	All other
CHF	92 ^b	0	8
Pulmonary disease	41 ^b	4	26
MI	54 ^b	30	22
PVD	30 ^b	18	12
Renal failure	31 ^b	23	9
Dementia	31 ^b	28	31 ^b
CVD	35	71 ^b	13
Paralysis	6	27 ^b	1
Diabetes	55	60 ^b	25
Hypertension	93	98 ^b	72
Cancer	21	22 ^b	17
Class assignment (%) ^c	18	16	66

Note. *N* = 470. Entries are percentage of cases within class with the condition; for example, 92% of members in the Cardiopulmonary class have the ICD 10 code corresponding to CHF. Only the highest percentage among all classes is given. CHF = congestive heart failure. CVD = cerebrovascular disease; MI = myocardial infarction; PVD = peripheral vascular disease.

^aIncludes paralysis.

^bHighest percentage among the classes.

^cPercentages are population estimates

TABLE 4

Characteristics Associated with Latent Class Membership

Characteristic	Cardiopulmonary (<i>n</i> = 85)		Cerebrovascular (<i>n</i> = 63)		All other (<i>n</i> = 322)		<i>p</i>
	<i>n</i>	(%)	<i>n</i>	(%)	<i>n</i>	(%)	
Age (years)							<.001
60–69	8	(9.4)	14	(22.2)	37	(11.5)	
70–79	38	(44.7)	20	(31.8)	70	(21.7)	
80–84	12	(14.1)	12	(19.0)	64	(19.9)	
85	27	(31.8)	17	(27.0)	151	(46.9)	
Gender							
Female	50	(58.8)	36	(57.1)	248	(77.0)	<.001
Male	35	(41.2)	27	(42.9)	74	(23.0)	
Race							<.01
White	34	(40.0)	23	(36.5)	182	(56.5)	
Black	39	(45.9)	28	(44.4)	95	(29.5)	
Other	12	(14.1)	12	(19.1)	45	(14.0)	
Ethnicity							
Non-Hispanic	65	(76.5)	52	(82.5)	260	(80.8)	
Hispanic	20	(23.5)	11	(17.5)	62	(19.2)	
Marital status							
Single	9	(10.6)	7	(11.1)	35	(10.9)	
Married	14	(16.5)	14	(22.2)	65	(20.2)	
Widowed	47	(55.3)	26	(41.3)	170	(52.8)	
D/S	15	(17.7)	16	(25.4)	51	(15.8)	
Education ^a							
<HS	21	(24.7)	14	(22.2)	62	(19.3)	
HS	31	(36.5)	26	(41.3)	130	(40.4)	
>HS	33	(38.8)	23	(36.5)	129	(40.1)	
Facility (type)							<.001
ALF	16	(18.8)	13	(20.6)	127	(39.4)	
NH	40	(47.1)	31	(49.2)	87	(27.0)	

Characteristic	Cardiopulmonary (<i>n</i> = 85)		Cerebrovascular (<i>n</i> = 63)		All other (<i>n</i> = 322)		<i>p</i>
	<i>n</i>	(%)	<i>n</i>	(%)	<i>n</i>	(%)	
HCBS	29	(34.1)	19	(30.2)	108	(33.5)	
Income (annual) (\$)							.06
0–9,999	30	(35.3)	24	(38.1)	76	(23.6)	
10,000–19,999	20	(23.5)	10	(15.9)	57	(17.7)	
20,000–29,999	6	(7.1)	5	(7.9)	16	(5.0)	
30,000–39,999	3	(3.5)	1	(1.6)	9	(2.8)	
40,000	5	(5.9)	6	(9.5)	48	(14.9)	
Unknown	21	(24.7)	17	(27.0)	116	(36.0)	
Medicaid ^b							<.01
No	30	(35.3)	29	(46.0)	173	(53.7)	
Yes	53	(62.4)	33	(52.4)	142	(44.1)	

Note. *N* = 470. Study participants were assigned to classes based on highest posterior probabilities of class membership and then classes were characterized using descriptive statistics. ALF = assisted living facility; D/S = divorced or separated; HCBS = home or community-based services; NH = nursing home.

^aEducational status of one participant in the All Other class was unknown.

^bMedicaid status was unknown for 2 cases in the Cardiopulmonary class, 1 case in the Cerebrovascular/Paralysis class, and 7 cases in the All Other class.

TABLE 5

Prediction of Number of Hospitalizations: Poisson Regression Analysis

Predictor	LC only			CCI only			LC and CCI		
	RR	(SE)	p	RR	(SE)	p	RR	(SE)	p
MCC Class									
Cardiopulmonary	1.88	(0.33)	<.001				1.74	(0.50)	ns
Cerebrovascular	1.17	(0.29)	ns				1.09	(0.34)	ns
All other	1.00	–	–				1.00	–	–
CCI ^a				1.10	(0.04)	.01	1.02	(0.06)	ns
GDS-SF	1.04	(0.02)	.02	1.04	(0.02)	.02	1.04	(0.02)	.02
LTSS (type)									
ALF	1.00	–	–	1.00	–	–	1.00	–	–
NH	1.56	(0.33)	.03	1.55	(0.32)	.03	1.55	(0.32)	.03
HCBS	0.73	(0.18)	ns	0.74	(0.18)	ns	0.73	(0.18)	ns

Note. N = 470. All models controlled for demographic characteristics, time of data collection, depressive symptoms, number of symptoms, and functional status. This table only shows significant findings. Complete statistical detail is available as Supplemental Digital Content 2 and 3. ALF = assisted living facility; CCI = Charlson Comorbidity Index; GDS-SF = Geriatric Depression Scale-SF; HCBS = home- or community-based services; LC = latent class; LTSS = long-term services and supports; MCC = multiple comorbidities; NH = nursing home; RR = relative ratio; SE = standard error.

^aCCI uses integer weights from 1–6, with a weight of 6 representing the most severe condition.