Original Article

JOURNAL OF MULTIMORBIDITY & COMORBIDITY

Chronic condition clusters and associated disability over time

Journal of Multimorbidity and Comorbidity
Volume 12: 1–8

DOI: 10.1177/26335565221093569
journals.sagepub.com/home/cob
SAGE

Tara C Klinedinst[1,2,*], Lauren Terhorst[3,4,5] and Juleen Rodakowski[3,5]

Abstract

Objectives: Recent evidence shows that more complex clusters of chronic conditions are associated with poorer health outcomes. Less clear is the extent to which these clusters are associated with different types of disability (activities of daily living (ADL) and functional mobility (FM)) over time; the aim of this study was to investigate this relationship.

Methods: This was a longitudinal analysis using the National Health and Aging Trends Study (NHATS) (n = 6179). Using latent class analysis (LCA), we determined the optimal clusters of chronic conditions, then assigned each person to a best-fit class. Next, we used mixed-effects models with repeated measures to examine the effects of group (best-fit class), time (years from baseline), and the group by time interaction on each of the outcomes in separate models over 4 years.

Results: We identified six chronic condition clusters: Minimal Disease, Cognitive/Affective, Multiple Morbidity, Osteoporosis, Vascular, and Cancer. Chronic condition cluster was related to ADL and FM outcomes, indicating that groups experienced differential disability over time. At time point 4, all chronic condition groups had worse FM than Minimal Disease.

Discussion: The clusters of conditions identified here are plausible when considered clinically and in the context of previous research. All groups with chronic conditions carry risk for disability in FM and ADL; increased screening for disability in primary care could identify early disability and prevent decline.

Keywords

activities of daily living, multimorbidity, disability, latent class analysis

An estimated 81% of adults aged 65 years and older in the United States have multiple chronic conditions (MCC), characterized by the presence of two or more chronic conditions in the same person.[1] Managing MCC is burdensome, both for the healthcare system and the individual; consequently, having MCC is associated with poor quality of life,[2] disability,[3] high health care utilization,[4] and high mortality.[5] Recent research suggests that certain chronic conditions may predictably co-occur, potentially due to common genetic, lifestyle and environmental propensities.[6] Researchers have identified clusters of co-occurring chronic conditions and linked these clusters to relevant health related outcomes, like health care utilization, quality of life, and independent living.[7–11] Though no definitive clusters of conditions have arisen from this research, there is support

[1]Department of Rehabilitation Sciences, University of Oklahoma Health Sciences Center, Tulsa, OK, USA
[2]OU-TU School of Community Medicine, Tulsa, OK, USA
[3]Department of Occupational Therapy, School of Health and Rehabilitation Science, University of Pittsburgh, Pittsburgh, PA, USA
[4]Department of Health and Community Systems, School of Nursing, University of Pittsburgh, Pittsburgh, PA, USA
[5]Clinical and Translational Science Institute, University of Pittsburgh, Pittsburgh, PA, USA

Corresponding author:
*Tara C Klinedinst, Department of Rehabilitation Sciences, University of Oklahoma Health Sciences Center, 4502 E. 41st Street, Tulsa, OK 74135, USA.
Email: tara-klinedinst@ouhsc.edu

for the idea that the impact of having MCC is greater than the cumulative effects of single diseases alone, and this research may indicate common pathways to disability.[6] Identifying clusters of chronic conditions may help identify groups with similar clinical trajectories and assist clinicians and health care systems to identify older adults who are in need of rehabilitation services in order to safely and independently age in community.

Carrying out activities of daily living (ADL; e.g., eating, dressing, bathing) and functional mobility (FM; getting around the house and community) are critical to aging in community, but require different mental and physical ability. For example, mental functions, like planning and sequencing, and fine motor skills are required to complete ADL independently, but balance and physical capacity are necessary for independent FM. Because of this difference, we hypothesize that certain clusters of chronic conditions may differentially impact ADL versus FM.

Similar research has been previously carried out in Spanish adults (aged 50 years and older). For these adults, multimorbidity clusters were associated with higher level of disability in ADL compared to the reference group ("healthy" adults) at baseline and at 3-years follow-up.[8] Though innovative in its science, this study was limited by a relatively young and healthy sample (63.8% of the sample was classified as healthy). Given these limitations, we need to understand how chronic conditions cluster together in a wide variety of older adults, and the influence of these clusters on longitudinal disability and FM outcomes. To understand the impact of MCC on disability and determine if common pathways to disability exist, we tested the extent to which chronic condition clusters are associated with different types of disability over time in older adults.

Therefore, the aim of this research is to first identify clusters of chronic conditions that tend to co-occur, then link these groups to ADL and FM disability trajectories. Understanding the extent to which specific clusters of chronic conditions are associated with types of disability over time will provide evidence for directing intervention efforts toward sub-populations who are at risk for disability and do not currently receive supports. This information is critical to clinicians who work with older adults with chronic conditions as well as policy makers who influence how rehabilitation services are administered.

Methods

Participants

This study uses data from the National Health and Aging Trends Study (NHATS). Started in 2011, the NHATS is an annual in-person survey of a nationally representative sample of older adults aged 65 years and older in the United States. The participants were 6179 older adults who were community-dwelling at baseline (round 5). We used the round five cohort (2015) as baseline because the NHATS sample was refreshed in round five and using this cohort promised the largest and most recent data set, then followed participants for three additional years to plot disability and FM data.

Chronic conditions variables and covariates

Presence of 11 individual chronic conditions. Yes/no to 'has a doctor ever told you that you have the following diseases': heart disease, high blood pressure, arthritis, osteoporosis, diabetes, lung disease, stroke, dementia, cancer, heart attack, and depression. These variables were obtained from the 2015 (round 5) cohort of NHATS and are the only chronic conditions collected by the survey. These dichotomous variables were entered into the latent class analysis (LCA) to identify clusters of chronic conditions that tend to co-occur.

Covariates. Gender (man vs woman), minority status (all races/ethnicities vs white), age in years at time of interview, and education level (at least some college vs. HS or less) were included as covariates in the LCA to aid in classification.[12]

Disability and FM variables

The outcome variables were obtained from the 2015 to 2018 (rounds 5–8) cohorts of NHATS.

Activities of daily living variable. The basic ADL variable was constructed from the Self-Care Activities scale of the NHATS. Participants reported any level of difficulty eating, showering, using the toilet, or dressing (1 = none, 4 = a lot) and those who do not complete self-care activities by themselves were assigned a 5. Possible range is 4–20, where higher scores indicate more difficulty with ADL.

Functional mobility variable. The FM variable was constructed from the mobility scale of NHATS. The variable was constructed using questions about difficulty accessing spaces inside and outside of the house by themselves. How much difficulty leaving the house to go outside, getting around inside the home, and getting out of bed (1 = none, 4 = a lot, those who reported they do not do these activities were assigned a 5). The possible range of this variable is 3–15, where higher scores mean worse FM.

Statistical analyses

Descriptive statistics. We performed descriptive statistics on this sample to determine baseline characteristics in age, number of comorbidities, gender, minority status, and education level stratified by class.

Latent class analysis. Latent class analysis is a statistical method used to determine if an unobserved (latent) variable exists within a set of variables by modeling probabilities of class (i.e., best-fit group) membership.[13] We first tested increasingly complex models, beginning with three groups and ending with six groups. We determined the optimal number of groups using the Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), entropy, and clinical interpretability.[7] The BIC reflects how well the model fits the data, and models with smaller BIC values are preferred. For clinical interpretability, we discussed whether each model had clinical significance (i.e., do these clusters make sense?). We included the covariates in the LCA to aid in classification, which provided us with odds ratios, a way to describe the likelihood of class membership of each covariate, using the minimal disease group as the reference. We used SAS PROC LCA, an add-in SAS procedure, to conduct the LCA.[12]

Growth curve modeling. We used repeated measures models with fixed and random effects to examine the impacts of group (chronic condition cluster), time (years from baseline), and the group x time interaction on each of the outcomes. We also included the random effect of individual variance in the model. Model parameters were estimated using full maximum likelihood technique. We tested the following distributions: negative binomial, gamma, and Poisson, and chose the best fit based on the model with the lowest BIC, and transformed least square estimates back to the original scale for interpretation. The outcomes for the growth curve models were our daily activity variables: FM and ADL. We also used post-hoc t-tests with adjustment for multiple comparisons to probe simple differences of least squares means to compare each group at each time point for each outcome. We excluded all participants in the growth curve trajectory who had less than two follow-up data points for the disability variables.[14] After excluding those individuals, we had less than 3% missing for chronic conditions and covariates, so we used pairwise exclusion. Sampling weights and covariates (gender, age, minority status, and education) were incorporated into the final models. We used SAS PROC GLIMMIX to model the group trajectories.

Results

Participants

Our final sample was 6171 older adults. The mean age was 77.9 years (SD = 7.6) and mean overall number of chronic conditions was 2.5 (SD = 1.5). Approximately 57% of the sample was female, and 31% was a racial or ethnic minority. Roughly half of the sample (51.4%) had at least some college education. For a complete breakdown of participant demographics by condition cluster, see Table 1.

Latent class analysis

Modeling the optimal number of groups. Clusters of chronic conditions were best modeled with six groups. The 6-group model was chosen by comparing AIC, BIC, entropy, and clinical meaningfulness among models with three through six groups without covariates. When our model included six groups versus five groups, a group with highest prevalence of depression and dementia emerged (our Cognitive/Affective group). Given previous research that demonstrates associations among individuals with cognitive/affective conditions and disability,[9] we concluded that this would be an important group to include in the model. Groups were named based on excess prevalence of disease compared to prevalence in the total sample. Bayesian Information Criterion for 3–6 group models without covariates are in Supplemental Table 1.

Characteristics of chronic condition groups. Our Minimal Disease group, named for having no excess prevalence of disease, made up nearly 34% of our sample (see Table 1 for sample characteristics and probabilities of class membership, and Table 2 for odds ratios for sociodemographic characteristics). These individuals were the youngest group (mean age = 75.2 years) and had an average of 1.5 chronic conditions. The Cognitive/Affective group had excess prevalence of every chronic condition, except diabetes and cancer, with the highest prevalence of depression and dementia across groups (4.8% of the sample). This group was the oldest (mean age = 86.8 years) and had the highest average number of chronic conditions (mean = 4.1). This group was disproportionately female with lower levels of education. We named the Multiple Morbidity group due to excess prevalence of heart disease, high BP, osteoporosis, diabetes, and depression, and highest probability of arthritis and lung disease (26.6% of the sample). Interestingly, our Multiple Morbidity group was almost exclusively comprised of women (97%) and was one of our older groups (mean age = 79.7 years). Our Osteoporosis group was disproportionately comprised of white women with at least some college education and had excess prevalence of cancer and the highest probability of osteoporosis (13.5% of the sample). On the other hand, our Vascular group, roughly 11% of the sample, was majority male (67%) and non-white (62%). We named this group Vascular due to excess prevalence of arthritis, lung disease, dementia, cancer, and depression, but highest prevalence of conditions that damage or result from damage to blood vessels: heart disease, high blood pressure, diabetes, stroke, and heart attack (10.9% of the

Table 1. Characteristics of study sample by best-fit class and probabilities of class membership based on excess prevalence of disease.

Demographic variable	Total sample	Minimal disease[a]	Cognitive/ Affective[b]	Multiple morbidity[c]	Osteoporosis[d]	Vascular[e]	Cancer[f]
N (%)	6171	2080 (33.7)	296 (4.8)	1640 (26.6)	835 (13.5)	671 (10.9)	649 (10.5)
Age, mean (sd)	77.9 (7.6)	75.2 (6.6)	86.8 (6.7)	79.7 (7.2)	75.7 (7.0)	76.6 (6.5)	81.7 (7.8)
Number chronic conditions, mean (sd)	2.5 (1.5)	1.5 (1.0)	4.1 (1.4)	3.4 (1.0)	1.7 (1.0)	4.0 (1.3)	2.1 (1.1)
Female, *n* (%)	3520 (57.0)	605 (29)	217 (73.3)	1590 (97.0)	835 (100)	168 (33.4)	105 (16.1)
Minority, *n* (%)	1937 (31.4)	753 (36.2)	142 (48.0)	585 (35.7)	30 (3.6)	413 (61.5)	14 (2.2)
At least some college, *n* (%)	3171 (51.4)	1121 (53.9)	82 (27.7)	683 (41.6)	637 (76.3)	175 (26.1)	473 (72.9)
Chronic condition	Prevalence in total sample	Prevalence of chronic condition by best-fit class					
Heart disease	20.4	0.0	28.1*	24.6*	4.4	45.3**	36.7*
High BP	70.8	57.7	81.2*	92.3*	38.5	93.3**	62.0
Arthritis	61.2	36.5	75.4*	88.4**	59.3	68.0*	47.4
Osteoporosis	24.1	1.6	44.2*	46.9*	50.1**	12.4	5.7
Diabetes	28.3	22.3	26.0	35.2*	1.5	62.1**	15.1
Lung disease	18.2	8.3	20.8*	28.1**	13.6	27.2*	16.0
Stroke	5.9	3.4	15.9*	5.6	1.2	19.4**	4.0
Dementia	6.1	1.3	69.1**	0.0	0.0	7.4*	1.0
Cancer	15.6	14.8	10.7	13.7	17.2*	23.5*	30.8**
Heart attack	8.2	2.2	9.8*	5.6	1.0	32.8**	19.7*
Depression	13.4	8.5	33.9**	17.0*	3.6	33.6*	1.3

Note. BP = blood pressure.
* excess prevalence of condition compared to overall sample.
** highest prevalence of condition.
Key for group naming.
[a] no excess prevalence of any disease
[b] highest prevalence of dementia and depression
[c] excess prevalence of gradual-onset chronic conditions
[d] highest prevalence of osteoporosis
[e] highest prevalence of conditions that damage or result from damage to blood vessels
[f] highest prevalence of cancer.

Table 2. Odds ratio estimates by group (95% confidence intervals).

Covariate	Cognitive/affective	Multiple morbidity	Osteoporosis	Vascular	Cancer
Age	1.24 (1.13, 1.36)	1.07 (1.03, 1.12)	1.02 (0.97, 1.08)	1.03 (0.99, 1.07)	1.11 (1.03, 1.19)
Minority status	1.67 (0.83, 3.36)	0.81 (0.39, 1.70)	0.14 (0.06, 0.32)	1.91 (1.02, 3.57)	0.12 (0.02, 0.57)
Sex, female	4.00 (0.75, 21.77)	22.94 (5.74, 94.36)	257.50 (0.19, 3577.85)	0.87 (0.47, 1.60)	0.69 (0.28, 1.68)
At least some college	0.51 (0.27, 0.95)	0.90 (0.52, 1.57)	1.93 (1.13, 3.29)	0.41 (0.24, 0.72)	1.78 (1.00, 3.19)

Note. With Minimal Disease group as reference category.

sample). Our Cancer group was relatively older (mean age = 81.7 years) with relatively fewer chronic conditions (mean = 2.1). This group was majority male (16.1% female) and white (97.8%). The Cancer group had excess prevalence of heart disease and heart attack, but highest probability of cancer (10.5% of the sample).

Median class membership probability for the sample was 0.72 (range = 0.29–1.00); this is the probability that individuals were assigned to the correct group. Therefore, at least 50% of the sample had 0.72 or greater probability of actual membership in the group to which they were assigned.

Table 3. Results from group x time interactions for FM.

Group	Time	β	SE	LSM	SE	95% CI	
Cognitive/Affective	1	1.47	0.05	4.35	0.20	3.99	4.74
	2	1.60	0.05	4.95	0.24	4.50	5.44
	3	1.66	0.06	5.24	0.28	4.72	5.82
	4	1.80	0.07	6.03	0.38	5.34	6.81
Multiple morbidity	1	1.43	0.03	4.18	0.11	3.98	4.40
	2	1.56	0.03	4.75	0.13	4.50	5.01
	3	1.59	0.03	4.89	0.15	4.62	5.19
	4	1.65	0.04	5.19	0.18	4.87	5.54
Osteoporosis	1	1.45	0.04	4.24	0.14	3.99	4.51
	2	1.59	0.04	4.89	0.17	4.58	5.22
	3	1.60	0.04	4.93	0.19	4.57	5.30
	4	1.68	0.05	5.34	0.23	4.92	5.80
Vascular	1	1.43	0.04	4.18	0.14	3.93	4.44
	2	1.61	0.04	4.98	0.18	4.65	5.33
	3	1.58	0.04	4.85	0.19	4.49	5.23
	4	1.73	0.05	5.60	0.24	5.15	6.09
Cancer	1	1.40	0.04	4.04	0.13	3.81	4.30
	2	1.55	0.04	4.68	0.16	4.39	4.98
	3	1.62	0.04	5.05	0.20	4.69	5.44
	4	1.66	0.05	5.25	0.22	4.84	5.68
Minimal disease	1	1.41	0.02	4.08	0.08	3.93	4.24
	2	1.55	0.03	4.69	0.10	4.50	4.89
	3	1.57	0.03	4.79	0.12	4.57	5.02
	4	1.39	0.03	4.00	0.10	3.81	4.19

Results for type III test of fixed effects

Group	Time	Group x time interaction
$F = 6.82$, $p < .001$*	$F = 156.86$, $p < .001$*	$F = 16.89$, $p < .001$*

Note. FM = functional mobility, LSM = least squares mean.

Table 4. Results from group x time interactions for ADL.

Group	Time	β	SE	LSM	SE	95% CI	
Cognitive/Affective	1	1.65	0.04	5.20	0.21	4.79	5.63
	2	1.80	0.05	6.03	0.28	5.51	6.59
	3	1.84	0.05	6.29	0.32	5.69	6.95
	4	1.85	0.05	6.34	0.35	5.70	7.06
Multiple morbidity	1	1.60	0.03	4.96	0.15	4.66	5.27
	2	1.74	0.03	5.71	0.18	5.38	6.07
	3	1.78	0.03	5.94	0.20	5.56	6.35
	4	1.81	0.04	6.11	0.22	5.70	6.56
Osteoporosis	1	1.61	0.03	4.98	0.16	4.67	5.31
	2	1.78	0.03	5.90	0.20	5.53	6.31
	3	1.78	0.04	5.92	0.22	5.51	6.36
	4	1.79	0.04	5.98	0.24	5.53	6.46
Vascular	1	1.60	0.03	4.98	0.15	4.68	5.29
	2	1.80	0.03	6.05	0.21	5.66	6.47
	3	1.76	0.04	5.83	0.22	5.42	6.28
	4	1.82	0.04	6.20	0.25	5.73	6.70
Cancer	1	1.57	0.03	4.81	0.14	4.54	5.10
	2	1.73	0.03	5.64	0.18	5.30	6.00
	3	1.83	0.04	6.25	0.23	5.83	6.71
	4	1.76	0.04	5.80	0.22	5.39	6.25
Minimal disease	1	1.59	0.03	4.89	0.14	4.63	5.17
	2	1.73	0.03	5.64	0.16	5.35	5.96
	3	1.76	0.03	5.84	0.18	5.50	6.20
	4	1.77	0.03	5.89	0.19	5.53	6.28

Results for type III test of fixed effects

Group	Time	Group x time interaction
$F = 1.33$, $p = .25$	$F = 331.36$, $p < .001$*	$F = 2.46$, $p = .001$*

Note. ADL = activities of daily living, LSM = least squares mean.

Growth curve models

We modeled each group's disability trajectory for ADL and FM. When comparing the BIC of different distributions, we found that our outcomes were best modeled using a gamma distribution for ADL and negative binomial for FM (Supplemental Table 1). The final follow-up assessment was conducted about 3 years following baseline. Table 3 and Table 4 report the betas with standard errors, least square means with standard errors and 95% confidence intervals for groups over time for both FM and ADL. Group by time interactions were significant for both FM and ADL (See Tables 3 and 4, respectively). When we probed simple differences between best-fit groups at each time point, we found at FM time point 4, all groups had differentiated from minimal disease. Cognitive/Affective ($\beta = 0.41$, SE = 0.06, $t = 7.15$, $p < .001$), Multiple Morbidity ($\beta = 0.26$, SE = 0.03, $t = 9.24$, $p < .001$), Osteoporosis ($\beta = 0.29$, SE = 0.04, $t = 7.89$, $p < .001$), Vascular ($\beta = 0.33$, SE = 0.04, $t = 9.33$, $p < .001$), and Cancer ($\beta = 0.0.27$, SE = 0.04, $t = 7.69$, $p < .001$) all had significantly worse FM than the Minimal Disease group. For ADL, we did not find significant differences between groups at time point 4.

Discussion

We used a data-driven clustering approach (LCA) to determine which chronic conditions tend to co-occur and then mapped out a 4-year disability trajectory for our outcomes: ADL and FM. We identified six different groups of chronic conditions; all groups carried risk for disability in ADL and FM that increased with time. At 4 years, all groups with MCC had worse FM than the minimal disease group. Having MCC has consistently been associated with worse health outcomes and increased health care utilization; our findings have important implications for how we distribute healthcare services and suggest a way to bolster disability

prevention and aging in community in older adults with MCC.

Our chronic condition groups roughly agree with previous work using LCA to identify clusters of disease.[7] For example, the minimal disease group was the largest group in this research, a result that replicates previous findings.[7,8,11,15] Additionally, a systematic review of multimorbidity clustering studies has identified two reliably-produced clusters: mental health disorders and cardio-metabolic.[16] These roughly relate to our Cognitive/Affective and Multiple Morbidity groups. These findings, alongside others, provide plausible evidence for the existence of groups of disease that tend to co-occur.[6,17] However, as a whole, studies using LCA to identify clusters of co-occurring conditions have yielded mixed results.[6] We hypothesize that differences in findings are due to differences in the sample (size and demographics) and variety of diseases counted. For example, variety of chronic conditions collected is highly dependent on the research study. Obesity, autoimmune disorders, and back/neck pain, which are common and potentially debilitating chronic conditions, have been collected by other researchers,[6] but not by NHATS. However, our disease groups are plausible when examined related to age and number of chronic conditions, and this alignment provides confidence that these clusters could reasonably predict longitudinal disability. These findings, considered in the context of previous work, are necessary to begin drawing connections among studies to identify clinical pathways to disability.

In the Vascular group, there was a high prevalence of older adults with diabetes. There is an established link between diabetes and vascular diseases, where oxidative stress and inflammation triggered by insulin resistance is thought to be a contributing factor.[18] In the Osteoporosis group, there is a high prevalence of both osteoporosis and cancer. Though it is impossible to say that one is a precursor to the other, the bone loss associated with cancer and cancer treatment could be one causal explanation for this link.[19] Alternatively, in the Cancer group, the highest prevalence of related chronic conditions were heart disease followed by heart attack. Interestingly, researchers have found elevated baseline levels of a biomarker (BNP; released when there is damage to the heart) in patients who later develop cancer when compared to those who have not developed cancer.[20] There was robust representation of cardiovascular diseases in the Cognitive/Affective group. Cardiovascular diseases are strongly implicated in development of dementia. However, research has suggested that lifestyle risk factors for cardiovascular disease may be more to blame than the disease itself.[21] Despite the linkages with biomarkers and inflammatory pathways, lifestyle factors may play as important of a role as physiology in development of chronic conditions. Smoking, poor nutrition, sedentary behavior, and excessive drinking are modifiable risk factors that contribute to nearly every chronic condition diagnosis studied here, and are likely actors in this research.[22] Despite the complexity of influences on disability, we demonstrated a longitudinal difference in FM using chronic conditions and sociodemographic factors to form our groups.

The results of our trajectory for FM indicated that some groups of individuals have disease and disabilities with gradual onset. These individuals may not present for hospital services and therefore are at risk of not being directed to appropriate rehabilitation services. Our Multiple Morbidity group, for example, was comprised of mostly women with excess prevalence of conditions with gradual-onset symptoms and disability (i.e., no excess prevalence of stroke, heart attack, or cancer). This group had roughly the same number of chronic conditions as our Vascular group (mean = 3.4 vs. 4.0) but was older (79.7 vs 76.6 years old). This finding suggests the presence of a group of older adults that have gradual-onset conditions that may be accompanied by gradual-onset disability. In our current hospital-based model of rehabilitation referral, this gradual-onset disability may progress undetected and untreated if no serious life-threatening medical intervention is required. Additionally, this group was heavily comprised of women; and there is a well-established phenomenon that women live longer than men, but with poorer health and more disability.[23,24] The needs of older adults with chronic health conditions are not likely to be effectively addressed without rehabilitation, raising the risk of increased disability, mortality, and institutionalization.[25] Increased screening for deficits in daily activity and FM in primary care could help identify early deficits and direct individuals to needed rehabilitation services.[26,27] Primary care, where the diagnosis and management of most health conditions takes place, remains a critical platform for identification of problems with function. To implement this change in rehabilitation services, clinicians should take advantage of existing but underused pathways for referral and reimbursement. For example, only 3–16% of eligible patients with chronic obstructive pulmonary disease are referred to pulmonary rehabilitation despite the overwhelming evidence of benefits to health and functional status.[28] Research indicates that lack of knowledge of available services is a primary reason for underutilization of these services.[29] Another reason may be limited access to rehabilitation resources, particularly in rural areas.[30] Equipping primary health care personnel to provide assessment of disability and functional capacity and increasing the workforce of rehabilitation professionals are two necessary actions to increase the capacity to provide adequate rehabilitative care.[25]

Interestingly, our Osteoporosis group had similar disability in FM to older groups with more mean chronic conditions. Though osteoporosis may not be disabling per se, it is a primary contributor to hip fracture, a highly debilitating acute injury. Hip fracture was not considered in this analysis because it is not a chronic condition, even though functional

deficits resulting from hip fracture can persist at least 2 years.[31] Women experience ¾ of all hip fractures, and a large proportion of those are attributed to osteoporosis.[32] Given this evidence, there is the possibility that osteoporosis progressed to hip fracture for many of the women in this group, which could have accounted for the similar disability in FM seen in this group and others with MCC.

In previous research, chronic condition groupings including cognitive and affective disorders have had lower ADL performance than other groups.[9] Given that our sample included only community-dwelling older adults, our Cognitive/Affective group was small (n = 296, 4.8% of the total sample). The small size of the group could mean there was insufficient data to detect a difference between this group and others. That said, when we examined graphs of the group trajectories, the Cognitive/Affective group consistently trended toward worse disability in FM and ADL than other groups.

We did not see significant differences between groups at time point 4 for ADL. We hypothesize that since these older adults were community-dwelling at baseline, disability in ADL was relatively low; after all, dependency in ADL is a primary predictor of nursing home admission.[33] The groups had significant increase over time in ADL disability and a significant difference between groups over time; however, at time point 4, these groups were not different. This may indicate short-term disability in ADL due to acute illness or surgery that was resolved over time.

Strengths, limitations, and future research

One strength of this research is the use of a large, nationally representative dataset. A few key limitations should be considered when interpreting these findings. First, it is important to note that while these clusters of conditions emerged based on presence of chronic conditions at baseline, movement among the groups that was not detected over the remaining three time points may have occurred. Despite this limitation, a clear separation in FM between groups with MCC and the minimal disease group was detected. Future researchers could use similar methods (e.g., latent transition analysis, clustering methods) to understand movement between groups over time. As noted previously, this study was limited to only 11 chronic conditions collected in this dataset. The possibility exists that individuals in our study have chronic conditions that are impacting daily functioning that are not represented here. For example, the Centers for Medicare and Medicaid Services recognizes 21 chronic conditions, including several mental health conditions. Further, chronic condition diagnosis is collected by self-report, as opposed to medical records or clinical examinations, which may have provided more accurate diagnoses. There are also some limitations related to the misclassification error. As indicated, the median class membership probability was .72, which means that the median probability of misclassification was .28. This error probability is similar to previous work,[7] where the authors indicated diminished enthusiasm for LCA based on this result. However, we believe that the value of this research lies in the ability of the chronic condition clusters to predict FM over 4 years, for which we found support. Other researchers have overcome high misclassification with fewer clusters, but these clusters are very broad, which may limit practical application.[8]

Conclusion

The pathways to disability are complex and intertwined; factors such as physiology, psychosocial, and sociodemographic status, and lifestyle factors are at the heart of the interaction between multimorbidity and functional impairment.[34] While we expected differences among groups based on number of chronic conditions and cognitive/affective impairment, we found was that all groups with MCC had worse FM than the minimal disease group at 4 years. This finding suggests that all clusters of multimorbidity carry risk for disability in FM. Some of these groups, for example, multimorbidity and osteoporosis, may not progress to life-threatening, acute events. However, these groups still carry risk for disability that may not be addressed in traditional, hospital-based rehabilitation referral systems. Integrating screening and rehabilitation services into primary care is one way to meet the needs of older adults who overwhelmingly prefer to age in community.[35]

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

This work was supported by the National Institute on Aging (grant number R01 AG056351). NHATS is sponsored by the National Institute on Aging (grant number U01AG032947) and the Johns Hopkins Bloomberg School of Public Health.

ORCID iD

Tara C Klinedinst https://orcid.org/0000-0002-2560-4631

Supplemental Material

Supplemental material for this article is available online.

References

1. Buttorff C, Ruder T and Bauman M. *Multiple chronic conditions in the United States*. Santa Monica, CA: RAND, 2017.
2. Makovski TT, Schmitz S, Zeegers MP, et al. Multimorbidity and quality of life: systematic literature review and meta-analysis. *Ageing Res Rev* 2019; 53: 100903.

3. Ryan A, Wallace E, O'Hara P, et al. Multimorbidity and functional decline in community-dwelling adults: a systematic review. *Health Qual Life Outcome* 2015; 13: 168–181, DOI: 10.1186/s12955-015-0355-9.
4. Wagner E, Patrick DL, Khandelwal N, et al. The influence of multimorbidity on health care utilization at the end of life for patients with chronic conditions. *J Palliative Med* 2019; 22: 1260–1265.
5. Willadsen TG, Siersma V, Nicolaisdóttir DR, et al. Multimorbidity and mortality: a 15-year longitudinal registry-based nationwide Danish population study. *J Comorbidity* 2018; 8: 2235042X18804063.
6. Prados-Torres A, Calderón-Larrañaga A, Hancco-Saavedra J, et al. Multimorbidity patterns: a systematic review. *J Clin Epidemiol* 2014; 67: 254–266.
7. Whitson HE, Johnson KS, Sloane R, et al. Identifying patterns of multimorbidity in older Americans: application of latent class analysis. *J Am Geriatr Soc* 2016; 64: 1668–1673, DOI: 10.1111/jgs.14201.
8. Olaya B, Moneta MV, Caballero FF, et al. Latent class analysis of multimorbidity patterns and associated outcomes in Spanish older adults: a prospective cohort study. *BMC Geriatr* 2017; 17: 186, DOI: 10.1186/s12877-017-0586-1.
9. Quiñones AR, Markwardt S, Thielke S, et al. Prospective disability in different combinations of somatic and mental multimorbidity. *J Gerontol Ser A* 2017; 73: 204–210, DOI: 10.1093/gerona/glx100.
10. Larsen FB, Pedersen MH, Friis K, et al. A latent class analysis of multimorbidity and the relationship to socio-demographic factors and health-related quality of life. A national population-based study of 162,283 Danish adults. *PloS One* 2017; 12: e0169426.
11. Park B, Lee HA and Park H. Use of latent class analysis to identify multimorbidity patterns and associated factors in Korean adults aged 50 years and older. *PloS One* 2019; 14: e0216259.
12. Lanza ST, Dziak JJ, Huang L, et al. *Proc LCA & Proc LTA users' guide (Version 1.3. 2)*. University Park, Penn State: The Methodology Center, 2015.
13. Lanza ST, Tan X and Bray BC. Latent class analysis with distal outcomes: a flexible model-based approach. *Struct Equat Model Multidisciplinary J* 2013; 20: 1–26.
14. Hesser H. Modeling individual differences in randomized experiments using growth models: recommendations for design, statistical analysis and reporting of results of internet interventions. *Inter Intervent* 2015; 2: 110–120, DOI: 10.1016/j.invent.2015.02.003.
15. Islam MM, Valderas JM, Yen L, et al. Multimorbidity and comorbidity of chronic diseases among the senior Australians: prevalence and patterns. *PloS One* 2014; 9: e83783.
16. Busija L, Lim K, Szoeke C, et al. Do replicable profiles of multimorbidity exist? Systematic review and synthesis. *Eur J Epidemiol* 2019; 34: 1025–1053.
17. Kirchberger I, Meisinger C, Heier M, et al. Patterns of multimorbidity in the aged population. Results from the KORA-Age study. *PloS One* 2012; 7: e30556.
18. Ormazabal V, Nair S, Elfeky O, et al. Association between insulin resistance and the development of cardiovascular disease. *Cardiovasc Diabetol* 2018; 17: 122–214.
19. Drake MT. Osteoporosis and cancer. *Curr Osteoporosis Rep* 2013; 11: 163–170.
20. Lau ES, Paniagua SM, Liu E, et al. Cardiovascular risk factors are associated with future cancer. *Cardio Oncol* 2021; 3: 48–58.
21. Fillit H, Nash DT, Rundek T, et al. Cardiovascular risk factors and dementia. *Am J Geriatr Pharmacother* 2008; 6: 100–118.
22. Ng R, Sutradhar R, Yao Z, et al. Smoking, drinking, diet and physical activity—modifiable lifestyle risk factors and their associations with age to first chronic disease. *Int J Epidemiol* 2020; 49: 113–130.
23. Newman AB and Brach JS. Gender gap in longevity and disability in older persons. *Epidemiol Rev* 2001; 23: 343–355.
24. Gordon E, Peel N, Samanta M, et al. Sex differences in frailty: a systematic review and meta-analysis. *Exp Gerontol* 2017; 89: 30–40.
25. World Health Organization. *Access to rehabilitation in primary health care: an ongoing challenge*. Geneva, Switzerland: WHO, 2018.
26. Morley JE, Arai H, Cao L, et al. Integrated care: enhancing the role of the primary health care professional in preventing functional decline: a systematic review. *J Am Med Directors Assoc* 2017; 18: 489–494.
27. Beaton K, McEvoy C and Grimmer K. Identifying indicators of early functional decline in community-dwelling older people: a review. *Geriatr Gerontol Int* 2015; 15: 133–140.
28. Morsø L, Qvist P and von Plessen C. *Overcoming challenges in early community rehabilitation of newly discharged patients with chronic obtructive pulmonary disease (COPD)*, 2016.
29. Molin KR, Egerod I, Valentiner LS, et al. General practitioners' perceptions of COPD treatment: thematic analysis of qualitative interviews. *Int J Chronic Obstructive Pulmon Dis* 2016; 11: 1929–1937.
30. Kamenov K, Mills J-A, Chatterji S, et al. Needs and unmet needs for rehabilitation services: a scoping review. *Disabil Rehabilitation* 2019; 41: 1227–1237.
31. Hallberg I, Rosenqvist AM, Kartous L, et al. Health-related quality of life after osteoporotic fractures. *Osteoporos Int* 2004; 15: 834–841.
32. Curtis JR and Safford MM. Management of osteoporosis among the elderly with other chronic medical conditions. *Drugs Aging* 2012; 29: 549–564.
33. Gaugler JE, Duval S, Anderson KA, et al. Predicting nursing home admission in the US: a meta-analysis. *BMC Geriatr* 2007; 7: 13–14.
34. Calderón-Larrañaga A, Vetrano DL, Ferrucci L, et al. Multimorbidity and functional impairment–bidirectional interplay, synergistic effects and common pathways. *J Int Med* 2019; 285: 255–271.
35. Harrell R, Lynott J, Guzman S, et al. *What is livable? Community preferences of older adults*. American Association of Retired Persons (AARP) Public Policy Institute, 2014.