MAYO CLINIC

ORIGINAL ARTICLE

Assessment of Common Comorbidity Phenotypes Among Older Adults With Knee Osteoarthritis to Inform Integrated Care Models

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Abstract

Objective: To establish the frequency of concordant, discordant, and clinically dominant comorbidities among Medicare beneficiaries with knee osteoarthritis (KOA) and to identify common concordant condition subgroups.

Participants and Methods: We used a 5% representative sample of Medicare claims data to identify beneficiaries who received a diagnosis of KOA between January 1, 2012, and September 30, 2015, and matched control group without an osteoarthritis (OA) diagnosis. Frequency of 34 comorbid conditions was categorized as concordant, discordant, or clinically dominant among those with KOA and a matched sample without OA. Comorbid condition phenotypes were characterized by concordant conditions and derived using latent class analysis among those with KOA.

Results: The study sample included 203,361 beneficiaries with KOA and 203,361 non-OA controls. The largest difference in frequency between the two cohorts was for co-occurring musculoskeletal conditions (23.7% absolute difference), chronic pain syndromes (6.5%), and rheumatic diseases (4.5%), all with a higher frequency among those with knee OA. Phenotypes were identified as low comorbidity (53% of cohort with classification), hypothyroid/osteoporosis (27%), vascular disease (10%), and high medical and psychological comorbidity (10%).

Conclusions: Approximately 47% of Medicare beneficiaries with KOA in this sample had a phenotype characterized by one or more concordant conditions, suggesting that existing clinical pathways that rely on single or dominant providers might be insufficient for a large proportion of older adults with KOA. These findings could guide development of integrated KOA-comorbidity care pathways that are responsive to emerging priorities for personalized, value-based health care.

 ■ Mayo Clin Proc Inn Qual Out 2021;5(2):253-264

Knee osteoarthritis (KOA) is a highly prevalent, costly, and disabling chronic musculoskeletal pain condition among older adults with substantial personal and public health burden.[1-3] For many, KOA is accompanied by comorbid chronic diseases that can negatively affect pain-related outcomes, quality of care delivery, and health care costs associated with the treatment of KOA.[4-6] However, clinical practice guidelines for KOA and many other medical conditions (eg, diabetes, hypertension) provide limited specific guidance on how to modify treatment to accommodate or offset the effects of comorbidities and their associated treatments.[7,8]

Guideline-adherent care for any one condition could lead to increased risk of harm if it conflicts with best practice for other comorbid health conditions (eg, 2 guideline-adherent pharmacological treatments with high risk of adverse interaction). Beyond risk of harm, comorbid conditions can also adversely affect prognosis and the effectiveness of interventions targeting KOA.[9-11] On the other hand, some interventions (eg, exercise) may have cross-cutting benefits across

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KOA and other chronic diseases. When guidelines do provide direction for condition comanagement,[12] poor communication among medical disciplines, and siloed care models often preclude effective comanagement. As a result, patients with KOA and additional comorbidity burden are at elevated risk for highly variable, ineffective, and potentially harmful care.[4]

Care pathways that integrate management of comorbid medical conditions have the potential to make care safer, more effective, and more patient centered. To plan for allocation of resources and to identify the appropriate provider mix for these integrated pathways, we must first determine which comorbid conditions are concordant with KOA.[13] As first outlined for diabetes management,[14] concordant conditions are those that share an overall pathophysiologic risk profile and are likely to have general similarities in disease management. In contrast, discordant conditions do not share a pathophysiological profile or treatment approach, and clinically dominant conditions require immediate attention (eg, cancer or heart failure) and preclude focus on less serious conditions such as KOA.[14] Concordant conditions are natural targets for integrated care because of their shared underlying pathophysiology, potential to influence KOA treatment outcomes, and shared management approaches.

Our study had two primary aims focused on better characterizing comorbidity patterns associated with KOA. First, we examined the frequency of concordant, discordant, and clinically dominant comorbidities among Medicare beneficiaries with KOA and a matched cohort without osteoarthritis (OA). Conditions with a higher frequency among the KOA group compared with the matched cohort would suggest high levels of concordance, and potentially be the most amenable for comanagement. Second, we aimed to identify common concordant condition phenotypes among individuals with KOA. Results of this study could potentially help to guide health care systems in the development of specific integrated comorbidity care pathways.

PARTICIPANTS AND METHODS

Data Source

This study used a 5% sample of Medicare Fee-for-Service (FFS) claims data during 2011-2015. This is a representative sample of Medicare beneficiaries that can be used to make inferences about the Medicare population in the United States. The dataset included Part A (inpatient) and Part B (outpatient) claims, outpatient revenue center claims, skilled nursing facility (SNF) claims, carrier claims, and home health agency claims. For 2015, only claims from the first three quarters of the year were used (ie, claims that include the International Classification of Disease, 9th Revision, Clinical Modification [ICD-9-CM] classification for diagnoses and procedures rather than ICD-10). Part D enrollment data were used to create enrollment-related variables, but were not otherwise used in this analysis.

Population

The study population included all Medicare beneficiaries with a diagnosis of KOA between January 1, 2012, and September 30, 2015. To be considered for the analysis, beneficiaries must have had at least one claim with a diagnosis of KOA where they (1) were enrolled in FFS parts A and B at the time of the claim, (2) had at least 1 year of FFS enrollment before the claim (hence the January 2012 start window; more information on the 1-year review period is presented later),[15] and (3) were age 65 years or older at the time of the claim. The age criterion was necessary to exclude younger beneficiaries who were eligible for Medicare for specific medical conditions (eg, end-stage renal disease) but were not the focus of this study.

The Duke University Institutional Review Board approved this study. Consent was not applicable, as the study used Medicare claims data.

Definitions

Knee Osteoarthritis. Beneficiaries were considered to have KOA if they had an inpatient, SNF, outpatient, or home health claim with either (1) an ICD-9 code of 715.x6 (OA

Mayo Clin Proc Inn Qual Out ■ April 2021;5(2):253-264 ■ https://doi.org/10.1016/j.mayocpiqo.2020.09.011
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of knee) or (2) ICD-9 codes of 719.46 (knee pain) and one of 715.x8 (OA at other specified sites), 715.x9 (OA at multiple sites), or 715.x0 (OA at unspecified site). To eliminate rule-out diagnoses, which are nonvalidated diagnostic codes often found in outpatient claims files, if a beneficiary's first record of KOA was at an outpatient visit, they must have had another encounter (of any type) meeting the inclusion criteria at least 30 days later.[16]

We set an additional criterion to ensure a 1-year review period for identifying comorbidities preceding a KOA claim.[17] We defined KOA using only encounters after the beneficiary had at least 1 year of FFS parts A B coverage. Importantly, we were not trying to identify new diagnoses of KOA, and this additional criterion would exclude only those individuals who did not have at least 1 year of coverage before any KOA claim.

Index Date. The date of first KOA diagnosis (after at least 1 year of FFS parts A and B coverage) is the index date—the date in reference to which other variables, such as comorbid conditions and subsequent health care resource use, were derived.

Comorbidities. We compiled a list of 34 comorbidities using two common comorbidity indices (Charlson and Elixhauser)[18,19] and through a literature search for conditions that are particularly relevant in the context of KOA, such as other chronic pain conditions.[20] We defined comorbidities using ICD-9-CM diagnosis codes, listed in Supplemental Appendix 1 (available online at http://mcpiqojournal.org). Beneficiaries were considered to have comorbidity if they had an inpatient, SNF, outpatient, or home health claim with the specified codes in the 12 months preceding or on the same day as the KOA index date. We again used the aforementioned procedure to exclude rule-out diagnoses. Exceptions to this rule, requiring only a single claim of any type (following the Centers for Medicare and Medicaid Services [CMS] Chronic Conditions Data Warehouse algorithm[21]), were congestive heart failure, dementia, angina, myocardial infarction, and anemia. Alcohol abuse and other drug abuse disorders could not be assessed because of CMS record redactions in 2012-2017 and were not included in this analysis. Because we intended to use these claims as a means for identifying and classifying overall comorbidity burden around KOA, we included diagnosis codes in any position on the claim.

Classification of Comorbidities

We used a typology for comorbidity classification outlined by Piette and Kerr[14] to define clinically dominant, concordant, and discordant conditions with KOA. We classified these conditions *a priori* on the basis of existing literature, theoretical models of comorbidity, and expert opinion. Figure 1 depicts the categorization of comorbid conditions. Clinically dominant conditions are so complex or serious (eg, malignant cancer) that they preclude a clinical focus on conditions such as KOA. Concordant conditions are those that share risk factors, underlying pathophysiological characteristics, clinical symptoms, or management plans. We made an additional consideration in defining concordant conditions based on their degree of symptom presentation. Conditions that are highly symptomatic could plausibly increase general psychological distress and reduce activity levels—two factors known to worsen KOA-related disability.[6,22,23] Therefore, conditions not directly concordant but that could contribute to worsening of OA-related symptoms were considered indirectly concordant. Discordant conditions were those not defined by the previous classifications, and they were generally unrelated to KOA.

Comparison Group: Patients Without OA

Classification of comorbidities as concordant or discordant in this study was largely informed by prior literature and expert opinion. However, an additional aim was to evaluate concordance empirically by examining the degree to which these conditions were uniquely present among individuals with OA. Results would provide strong support for developing pathways that included comanagement of highly concordant conditions with KOA. To identify conditions with high degrees of KOA concordance, we developed a comparison group of beneficiaries age 65 years or older without OA in the sample between January 2012 and September 2015. Considering the similar pathophysiologic

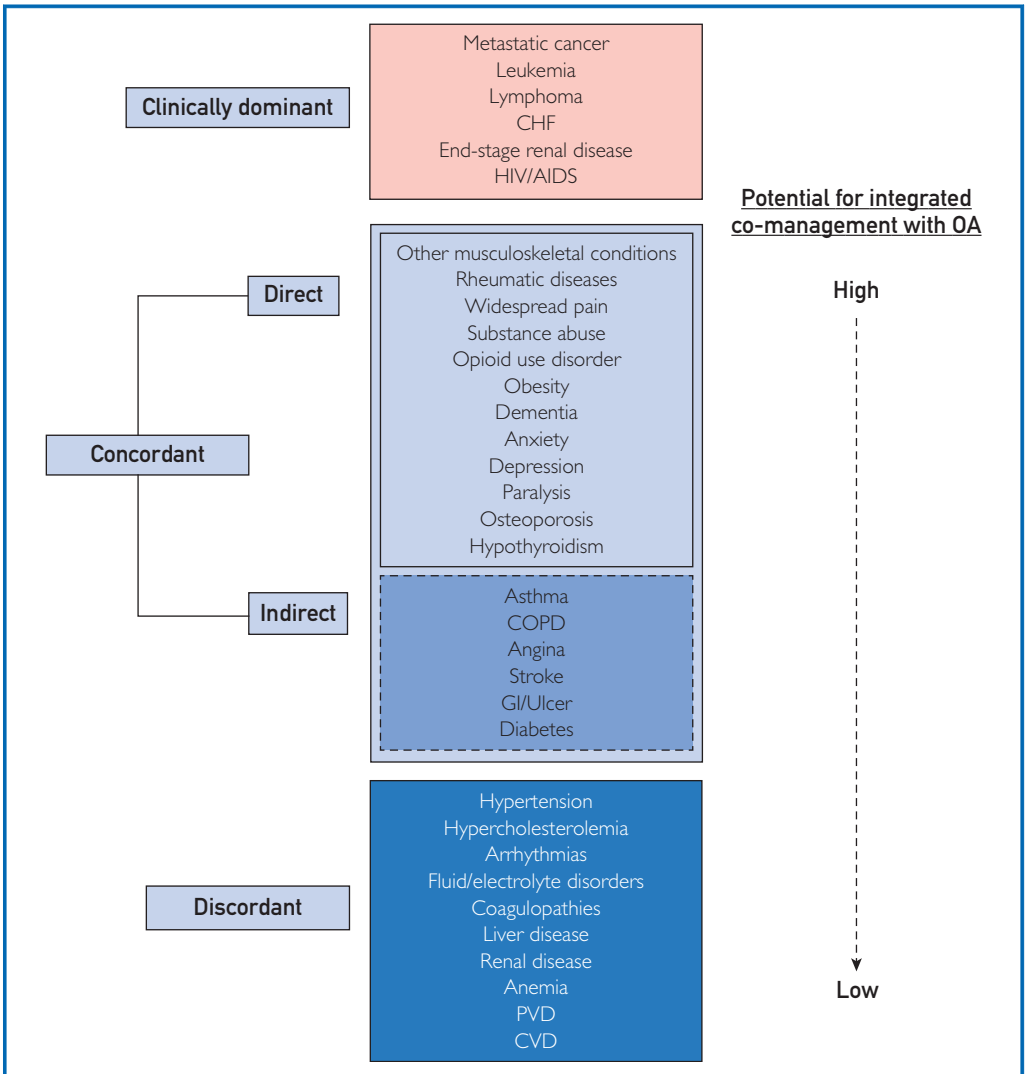

FIGURE 1. Osteoarthritis comorbidity conceptual model. CHF = congestive heart failure; COPD = chronic obstructive pulmonary disease; CVD = cardiovascular disease; GI = gastrointestinal; HIV/AIDS = human immunodeficiency virus/acquired immunodeficiency syndrome; OA = osteoarthritis; PVD = peripheral vascular disease.

processes and risk factors underlying OA across different anatomical sites (eg, KOA, hip OA, shoulder OA), we decided on a comparison group without any claim for OA in any anatomic region. By excluding other OA conditions in the comparison sample, we were better able to distinguish potentially unique relationships between KOA and non-OA conditions. Therefore, beneficiaries in the comparison group did not have any claim with an ICD-9 code of 715.x at any time and had at least 1 year of enrollment in FFS parts A and B enrollment (beginning January 1, 2011). Additional details on development of this comparison cohort are provided in Supplementary Appendix 2 (available online at http://mcpiqojournal.org).

Matching

For each beneficiary with KOA, a non-OA beneficiary must have met the same general eligibility criteria for the KOA cohort and was

Mayo Clin Proc Inn Qual Out ■ April 2021;5(2):253-264 ■ https://doi.org/10.1016/j.mayocpiqo.2020.09.011
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TABLE 1. Description of Beneficiaries With Knee Osteoarthritis and Matched Cohort of Beneficiaries Without Osteoarthritis (Variables Used in Matching)[a,b]

Variable[c]	Beneficiaries with KOA	Beneficiaries without OA	Standardized difference, %[d]
N	203,361	203,361	
Demographics			
Age, years	76.0 (7.7)	75.6 (7.7)	4.5
Female	68 (138,841)	68 (138,841)	0.0
White race	87 (175,968)	87 (175,968)	0.0
Resides in a rural area	24 (48,831)	25 (50,561)	2.0
Dual eligibility for Medicare and Medicaid	15 (30,302)	14 (29,287)	1.4
Study calendar time (since 1/1/2012 to index date), years	1.2 (1.0)	1.2 (0.9)	0.9
Health care encounters in previous 12 months			
One or more inpatient stays	25 (50,660)	25 (50,660)	0.0
Number of outpatient encounters	10.7 (6.5)	10.3 (6.5)	5.8
<10 outpatient encounters[e]	50 (100,796)	52 (106,213)	5.3
Use of a home health agency	16 (33,171)	16 (33,171)	0.0

[a]KOA = knee osteoarthritis; OA = osteoarthritis.
[b]See Supplemental Appendix 3 (available online at http://mcpiqojournal.org) for a summary that includes differences before matching.
[c]Age, study calendar time, and number of outpatient encounters are shown as mean (SD), all others as % (n).
[d]% Standardized difference = 100 × |mean(Group 1) − mean(Group 2)| / sqrt((var(Group 1) + var(Group 2)) / 2). For categorical variables, proportions are used rather than means. All standardized differences less than 10% are generally considered a good match.
[e]0 is the median in the pre-match knee-OA group. This is presented solely as an additional summary statistic; number of outpatient encounters was considered as continuous for matching.

selected according to criteria outlined in Supplementary Appendix 3 (available online at http://mcpiqojournal.org). Nearest neighbor matching was conducted using Mahalanobis distances.[24] Patients were matched in a 1:1 ratio in order of descending age to afford the oldest patients, who are the hardest to match because of the fewest potential matches, the largest possible pool of matches. For a small proportion (5%) of beneficiaries with KOA, there were no non-OA beneficiaries meeting the first two criteria. These beneficiaries with KOA were dropped from the final analysis cohort. Additional details of the matching process are provided in Supplementary Appendix 3 (available online at http://mcpiqojournal.org).

Missing Data

There were no missing data, with the exception of the "unknown" race category (<1% of patients). Other demographics (eg, age, sex, region) are complete in the CMS files. Comorbidities were determined as the presence or absence of specific types of previous claims and so cannot, by definition, be missing.

Comorbidity Phenotypes

Latent class analysis (LCA) was used to identify phenotypes defined by common distributions of the concordant (direct or indirect) comorbidity diagnoses, as these would be most amenable for integrated care. LCA defines classes by patterns of conditional probabilities for having specific characteristics, in this case the presence of diagnosis indicators.[25]

As a preliminary step, frequencies of different comorbidities in the KOA cohort were examined in two ways. First, any comorbidity occurring in fewer than 5% of beneficiaries was omitted from further consideration, a common approach to improve LCA model performance and to enhance the potential for replication of findings.[26-30] Second, comorbidities occurring at notably lower rates in our cohort than published rates in similar populations were removed, as it might reflect the inability to accurately identify the condition using ICD-9 codes alone.

All remaining candidate comorbidities were entered into the LCA procedure. Multiple

TABLE 2. Comorbidities Among Beneficiaries With Knee Osteoarthritis and Matched Cohort of Beneficiaries Without Osteoarthritis[a,b]

Variable	Beneficiaries with KOA	Beneficiaries without OA	Difference
N	203,361	203,361	
Clinically dominant conditions			
Congestive heart failure	15.3 (31,188)	18.1 (36,825)	−2.8
Any malignancy	10.7 (21,687)	16.9 (34,395)	−6.2
Metastatic solid tumor	0.9 (1851)	3.7 (7518)	−2.8
HIV/AIDS	0.1 (127)	0.1 (234)	0
Concordant/direct conditions			
Other musculoskeletal conditions	**75.8 (154,109)**	**52.1 (106,020)**	**23.7**
Hypothyroidism	**21.1 (42,939)**	**20.0 (40,721)**	**1.1**
Chronic pain syndrome	**13.6 (27,651)**	**7.1 (14,401)**	**6.5**
Depression	**12.5 (25,475)**	**10.7 (21,776)**	**1.8**
Osteoporosis	**11.3 (23,056)**	**9.2 (18,703)**	**2.1**
Obesity	9.8 (19,847)	5.4 (10,881)	4.4
Anxiety	**9.2 (18,754)**	**8.5 (17,385)**	**0.7**
Rheumatic diseases	**8.2 (16,608)**	**3.7 (7592)**	**4.5**
Dementia	**7.8 (15,936)**	**11.1 (22,530)**	**−3.3**
Other neurological disorders	**4.6 (9365)**	**6.3 (12,783)**	**−1.7**
Psychoses	2.6 (5305)	3.1 (6355)	−0.5
Pelvic pain syndrome	1.4 (2837)	1.1 (2257)	0.3
Paralysis	1.0 (2134)	1.4 (2943)	−0.4
Concordant/indirect conditions			
Diabetes	**29.3 (59,685)**	**31.2 (63,532)**	**−1.9**
Chronic pulmonary disease	**18.6 (37,873)**	**22.6 (45,936)**	**−4.0**
Peripheral vascular disease	**15.0 (30,594)**	**15.3 (31,213)**	**−0.3**
Cerebrovascular disease	**11.8 (23,927)**	**14.2 (28,944)**	**−2.4**
Myocardial infarction	**5.7 (11,507)**	**7.5 (15,216)**	**−1.8**
Angina	**5.6 (11,352)**	**5.8 (11,807)**	**−0.2**
Gastrointestinal/ulcer	1.6 (3289)	1.4 (2869)	0.2
Discordant conditions			
Hypertension	71.4 (145,173)	69.0 (140,378)	2.4
Dyslipidemia	59.3 (120,650)	56.7 (115,326)	2.6
Arrhythmias	21.4 (43,438)	24.9 (50,736)	−3.5
Fluid/electrolyte disorders	12.7 (25,838)	15.3 (31,019)	−2.6
Anemia	13.0 (26,405)	13.3 (27,017)	−0.3
Renal disease	11.5 (23,361)	13.9 (28,192)	−2.4
Valvular disease	11.1 (22,590)	13.1 (26,541)	−2.0
Coagulopathies	3.8 (7812)	4.8 (9697)	−1.0
Liver disease	3.0 (6128)	4.1 (8350)	−1.1
Pulmonary circulation disorders	2.7 (5560)	3.8 (7663)	−1.1

[a]HIV/AIDS, human immunodeficiency virus/acquired immunodeficiency syndrome; KOA, knee osteoarthritis; OA, osteoarthritis.
[b]Boldface terms are conditions included in latent class analysis. Values are shown as % (n) except where indicated.

models were generated, beginning with two classes and increasing until the magnitude of the likelihood ratio test statistic (G^2), relative to the degrees of freedom (df), leveled off.[31] Specifically, the plot of number of classes versus G^2/df was examined, visually, to determine at which point the slope between each pair of number-of-class points became noticeably shallower (ie, "leveled off).[32,33]

Considerations in selection of the final model included (1) goodness-of-fit measures (eg, sample size-adjusted Bayesian information criterion); (2) likelihood ratio tests to compare the fit of model with $k + 1$ classes to one with k classes, using 100 bootstrap samples[25,34]; (3) misclassification error rate; (4) interpretability of classes; and (5) class size.[30,31,35] After selecting the best model, beneficiaries were

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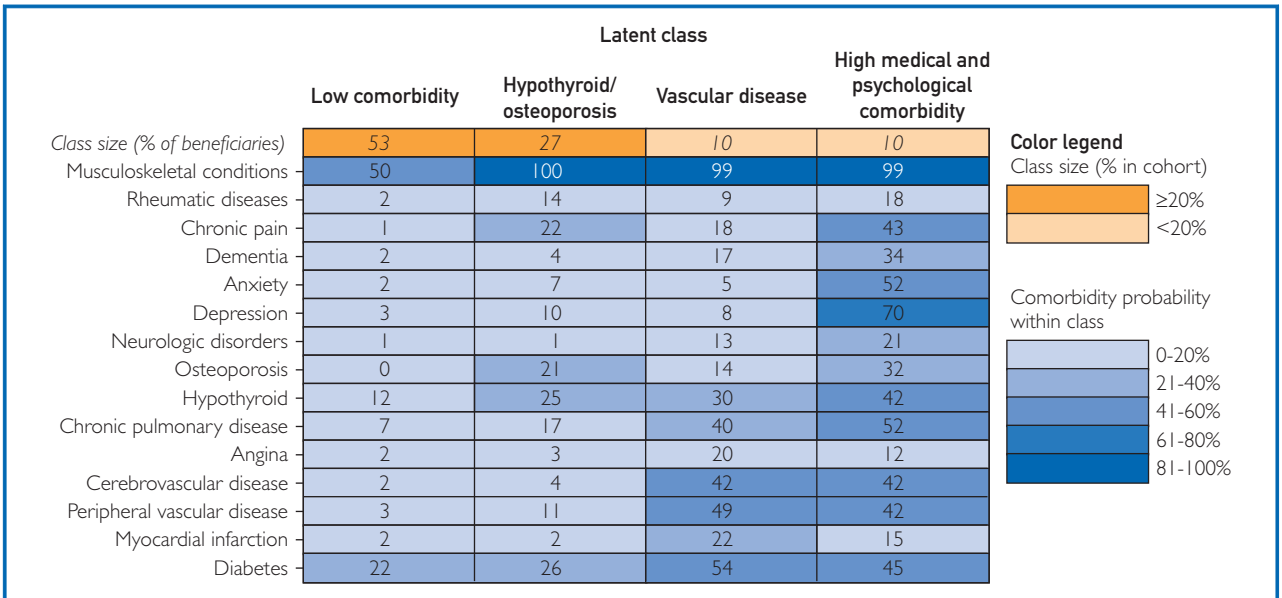

FIGURE 2. Probability of each comorbidity given latent class: 4-class model.

assigned to classes based on highest posterior probability.[36] All analyses were conducted using SAS software version 9.4 (Cary, NC) and the SAS procedure PROC LCA (The Methodology Center, Pennsylvania State University). The Duke University Institutional Review Board approved this study.

RESULTS

Frequency Rates Among KOA and Non-OA Cohorts

We identified 216,878 beneficiaries with KOA and 883,381 beneficiaries without OA. After matching, the study sample included 203,361 beneficiaries with KOA and 203,361 non-OA controls. The results of the generation of the matched cohorts are provided in Table 1. Standardized differences are shown with all being less than 10%, which is generally considered a good match. Table 2 compares comorbidity frequencies between cohorts. The largest difference in frequency between the two cohorts was for co-occurring musculoskeletal conditions (23.7% absolute difference), chronic pain syndromes (6.5%), and rheumatic diseases (4.5%), all with a higher frequency among those with KOA.

Identification of Latent Classes

Pelvic pain syndrome, psychoses, paralysis, and gastrointestinal or ulcer disease occurred in fewer than 5% of beneficiaries, who were omitted from further consideration. Although most comorbidity rates were within a reasonable range of published rates (Supplemental Appendix 4 available online at http://mcpiqojournal.org), obesity occurred at a much lower rate in our cohort (10% vs 35% reported by the Centers for Disease Control and Prevention in older adults). Given that identifying obesity from claims is often problematic, obesity was dropped from consideration for LCA.[37,38]

We evaluated model fit for various class sizes from 2 through 8. Beginning with 4 classes, the models all divided the beneficiaries into classes of approximately 50%, 25%, and 25%, with the models for 4 or more classes differing only in how they split the last 25% (Supplemental Table 1). Class sizes dictated that models with 4 or 5 classes should be considered. A marked decrease in the slope of the plot for the model fit indices between 4 and 5 classes supported this conclusion (Supplemental Figure 1, available online at http://mcpiqojournal.org).

TABLE 3. Beneficiary Characteristics by Comorbidity Class

Variable	All	Low comorbidity	Hypothyroid/osteoporosis	Vascular disease	High medical and psychological comorbidity
No. (%)	203,361 (100)	107,107 (53)	55,814 (27)	20,266 (10)	20,174 (10)
Demographics					
Age, y	75 (69, 82)	74 (69, 80)	75 (69, 82)	79 (73, 85)	78 (71, 85)
Female	68.3 (138,841)	64.1% (68,685)	76.5% (42,680)	58.4% (11,840)	77.5% (15,636)
Race					
White	86.5 (175,968)	87.1% (93,281)	86.8% (48,465)	81.1% (16,443)	88.1% (17,779)
Black	8.4 (17,068)	8.0% (8,585)	7.9% (4,382)	12.9% (2,624)	7.3% (1,477)
Other	5.1 (10,325)	4.9% (5,241)	5.3% (2,967)	5.9% (1,199)	4.6% (918)
Geographic region					
Northeast	19.6 (39,806)	18.8% (20,110)	20.7% (11,551)	21.5% (4,364)	18.7% (3,781)
Midwest	24.1 (48,953)	24.3% (26,076)	23.1% (12,901)	24.5% (4,972)	24.8% (5,004)
South	39.5 (80,345)	39.1% (41,907)	39.2% (21,860)	39.5% (8,014)	42.5% (8,564)
West	16.6 (33,772)	17.6% (18,803)	16.7% (9,330)	14.0% (2,847)	13.8% (2,792)
US Territory	0.2 (485)	0.2% (211)	0.3% (172)	0.3% (69)	0.2% (33)
Resides in a rural area	24.0 (48,831)	25.5% (27,314)	23.3% (13,030)	20.6% (4,167)	21.4% (4,320)
Dual eligible for Medicare and Medicaid	14.9 (30,302)	9.8% (10,458)	15.7% (8,776)	24.3% (4,934)	30.4% (6,134)
All health encounters in prior 12 months					
One or more inpatient stays	24.9 (50,660)	6.0% (6,436)	29.6% (16,524)	60.9% (12,332)	76.2% (15,368)
Number of outpatient encounters	10 (6, 15)	8 (5, 12)	12 (8, 17)	13 (8, 20)	13 (7, 20)
Use of a home health agency	16.3 (33,171)	3.2% (3,394)	18.5% (10,349)	38.5% (7,796)	57.7% (11,632)

Continuous variables are shown as median (25^{th}, 75^{th} percentiles); other values are % (No.) except where indicated.

We next evaluated the distribution of conditions within each class to assess their clinical interpretation and plausibility. The 5-class model identified a small (6%) but clinically meaningful class defined primarily by high probabilities of anxiety, depression, and chronic pain conditions. These conditions have shared underlying physiological mechanisms and a robust literature base linking them to the maintenance of OA-related disability.[5,22,23] However, smaller group sizes (<10%), lower posterior probabilities, and a higher misclassification rate in the 5-class model suggested that the 4-class model was preferable.

The four classes were identified as low comorbidity (53% of cohort), hypothyroid/osteoporosis (27%), vascular disease (10%), and high medical and psychological comorbidity (10%; Figure 2; Supplemental Table 2). Median of posterior probabilities used to assign class membership was 0.71 (interquartile range, 0.65-0.98; Supplemental Table 3, available online at http://mcpiqojournal.org). Selected demographic information for the classes is provided in Table 3.

DISCUSSION

These results highlight the substantial potential to improve care for older adults with KOA by aligning providers across disciplines to deliver strategic condition comanagement. Almost 50% of Medicare beneficiaries with KOA in this sample had a phenotype characterized by one or more concordant conditions, suggesting that perpetuation of existing management models that rely on single (or dominant) specialty providers are insufficient for a large proportion of older adults with KOA. Key comorbidity differences among older adults with KOA compared to those without OA included a higher frequency of other musculoskeletal conditions, rheumatic diseases, and chronic pain, which were especially prevalent in the hypothyroid/osteoporosis and high comorbidity phenotypes. These conditions

Mayo Clin Proc Inn Qual Out ■ April 2021;5(2):253-264 ■ https://doi.org/10.1016/j.mayocpiqo.2020.09.011
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provided the strongest evidence to better explain the spectrum of disease burden for KOA when compared to those without OA. Other common concordant conditions representing the most promising targets for comanagement based on frequency data included diabetes, hypothyroidism, chronic pulmonary disease, and peripheral vascular disease.

Care pathways that were structured to provided integrated condition comanagement for KOA would be responsive to value-based payment models that incentivize holistic, person-centered treatment, such as the capitated payment arrangements common in Medicare Advantage plans.[39] As enrollment in these plans grows,[40] it will become imperative to build integrated comanagement models and to test their ability to contain costs and enhance treatment outcomes.

Building care pathways that successfully deliver comanagement based on comorbidity phenotypes would require a team-based approach among disciplines. Importantly, a team-based approach is not separate providers working in series, but in parallel comanagement involving active collaboration among disciplines. Ideally, such an approach would also entail integrated, person-centered care delivery. One exemplar of integrated comanagement is the Assistance with Pain Treatment (APT) program described in Veteran's Health Administration primary care settings to treat patients with chronic musculoskeletal pain.[41,42] The APT team includes an internist, clinical psychologist, and care manager who collaborate to identify patient needs and to deliver or coordinate services. Although the APT model is focused on comanagement of psychological and behavioral needs associated with chronic musculoskeletal pain, a framework like this could be adapted for management of other medical comorbidities, such as the concordant conditions identified in this analysis.

Integrated comanagement would consist of a "core" team of OA providers including an orthopedist or rheumatologist, or both, along with one or more nonpharmacologic OA providers (eg, physical therapist, acupuncturist, clinical psychologist). The matching of additional disciplines forming the comanagement team would be based on phenotype. For instance, a comanagement care pathway for the second largest phenotype (ie, characterized by predominantly female beneficiaries with high probabilities of hypothyroid disease, osteoporosis, chronic pain, and diabetes) might include endocrinologists delivering metabolic or hormonal interventions plus physical therapists or orthopedists delivering KOA treatments focused on maintaining bone health and regular exercise. For the phenotype characterized by high probabilities of vascular and cardiac conditions, additional team members might include cardiologists and nontraditional OA providers, such as health coaches, exercise physiologists, and dietitians to deliver appropriate pharmacologic comanagement, exercise prescription, and lifestyle modification. An integrated care pathway for this phenotype would be a high priority given the substantial costs and health burden associated with both OA and cardiovascular disease.[43]

One important strength of this study is that it used a typology for classification of comorbidities that provides guidance on which conditions might be most amenable to comanagement—a novel approach to comorbidity classification in KOA. Previous studies have evaluated comorbidity profiles among general populations of older adults,[44,45] including those with OA,[4,46-48] but none has focused on concordant comorbid conditions in a KOA population. This issue was not addressed in our previous work on comorbidity phenotyping,[4] and the current study focused on identifying medical conditions concordant with OA to better guide health care delivery and policy regarding comanagement. Other classification schemes such as comorbidity counts and weighted indices do not fully account for complex interactions among medical conditions, highlighting one of the inherent limitations of current risk adjustment and evaluation processes.[13,14,49]

An additional strength of this study is the robust dataset used to evaluate health care use in older adults and to develop a matched comparison group. As a result, we have a strong indication of which conditions are likely to be unique among older

adults with KOA compared to those without OA. We focused on KOA in this analysis, but it is likely that many of these phenotypes, and certainly this methodology, could apply more broadly across other conditions and populations, as evidenced by a recent study that found similar comorbidity groups among individuals with low back pain.[4]

Limitations of this study include the derivation of small phenotype groups (10%), which may be difficult for some health care organizations to use as a basis for models because of lower patient volumes. We established concordance and discordance based on literature review and expert opinion, but we acknowledge the inherent subjectivity of these classifications. There are also common limitations with using claims data to identify diagnoses given the variability in clinical coding procedures.[50] Claims data do not include information on OA or symptom severity, which could limit our ability to describe the clinical presentation of these phenotypes in more detail. However, because severity does not solely dictate intensity of health care service use or level of disability, we do not believe that the absence of these variables detracts from the utility or implementation potential of condition comanagement. Characteristics like OA severity and body mass index, which is also not measurable through claims, would be important to consider in any comanagement strategy regardless of phenotype. Future studies should include measures of joint disease or symptom severity to better characterize these comorbidity subgroups and to guide the selection of specific treatments within each management pathway.

One assumption of working with claims data is that providers would include diagnoses on claims that are (1) relevant to the care being provided and (2) significant enough for patients to report to their provider. We intentionally chose to be inclusive of all diagnoses listed in the claims to better understand the full comorbidity profiles of individuals seeking care with KOA. This is not to say that patients were actively seeking care for all comorbid conditions, although many coexisting conditions could be considered chronic (eg, heart disease, diabetes, osteoporosis) and would require ongoing management. What these results tell us more generally is which conditions might need to be considered as part of a patient-centered condition comanagement plan for individuals with KOA. We took careful steps to ensure that we were appropriately identifying diagnoses, including exclusion of rule-out diagnoses and comparisons to known prevalence rates.

CONCLUSION

Existing clinical care delivery that relies on a single or dominant specialty providers could be insufficient for a significant proportion of older adults with KOA that have coexisting conditions. Development and implementation of integrated KOA comorbidity care pathways would address emerging priorities for personalized, value-based health care. Future work to develop and test integrated KOA comorbidity care delivery will require collaboration of multiple disciplines to understand what is feasible in an integrated model.

SUPPLEMENTAL ONLINE MATERIAL

Supplemental material can be found online at http://mcpiqojournal.org. Supplemental material attached to journal articles has not been edited, and the authors take responsibility for the accuracy of all data.

Abbreviations and Acronyms: **APT** = Assistance with Pain Treatment; **CMS** = Centers for Medicare and Medicaid Services; **FFS** = Medicare Fee-for-Service; **KOA** = knee osteoarthritis; **LCA** = latent class analysis; **OA** = osteoarthritis; **SNF** = skilled nursing facility

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Potential Competing Interests: The authors report no competing interests.

Grant Support: This work was supported by the Duke Clinical Research Institute (DCRI), where Drs. Lentz, Goode, and George and Ms. Hellkamp are employed.

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