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RESEARCH ARTICLE

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Using the Functional Comorbidity Index with administrative workers' compensation data: Utility, validity, and caveats

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Abstract

Background: Chronic health conditions impact worker outcomes but are challenging to measure using administrative workers' compensation (WC) data. The Functional Comorbidity Index (FCI) was developed to predict functional outcomes in community-based adult populations, but has not been validated for WC settings. We assessed a WC-based FCI (additive index of 18 conditions) for identifying chronic conditions and predicting work outcomes.

Methods: WC data were linked to a prospective survey in Ohio ($N = 512$) and Washington ($N = 2,839$). Workers were interviewed 6 weeks and 6 months after work-related injury. Observed prevalence and concordance were calculated; survey data provided the reference standard for WC data. Predictive validity and utility for control of confounding were assessed using 6-month work-related outcomes.

Results: The WC-based FCI had high specificity but low sensitivity and was weakly associated with work-related outcomes. The survey-based FCI suggested more comorbidity in the Ohio sample (Ohio mean = 1.38; Washington mean = 1.14), whereas the WC-based FCI suggested more comorbidity in the Washington sample (Ohio mean = 0.10; Washington mean = 0.33). In the confounding assessment, adding the survey-based FCI to the base model moved the state effect estimates slightly toward null (<1% change). However, substituting the WC-based FCI moved the estimate away from null (8.95% change).

Conclusions: The WC-based FCI may be useful for identifying specific subsets of workers with chronic conditions, but less useful for chronic condition prevalence. Using the WC-based FCI cross-state appeared to introduce substantial confounding. We strongly advise caution—including state-specific analyses with a reliable reference standard—before using a WC-based FCI in studies involving multiple states.

KEYWORDS

administrative data, chronic health conditions, Functional Comorbidity Index, workers' compensation

1 | INTRODUCTION

Chronic health conditions are increasingly prevalent in the workforce. In national surveys, roughly half of workers report having at least one chronic condition; roughly a quarter report more than one (multimorbidity).[1,2] Chronic condition prevalence increases with age,[3] weighing heavier on society as the workforce ages.[4] National estimates for workforce prevalence of specific chronic conditions vary by data source, but range from: 11% to 13% for asthma,[5,6] 5% to 8% for diabetes,[1,2,5,6] 7% for arthritis,[2] (25% among workers ages 50–64[1]), 9% to 14% for depression,[2,6] 8% for heart disease,[1] 13% for hearing impairment,[5] and 8% for chronic severe low back pain.[5]

US workers with chronic conditions are burdened with more work injuries[7,8] and more health care utilization.[2] In a national survey, workers ages 50–64 with multimorbidity had 2.6 times the mortality risk of workers with no chronic conditions, and 1.5 times the mortality risk of workers with one condition.[1] Chronic conditions are also associated with negative employment outcomes, including presenteeism, absenteeism, work disability, unemployment, fewer work hours, lower earnings, early retirement, and disability benefits/pension.[1,3,9–14] Impact varies by condition[15–17]; chronic back/neck pain, arthritis, and mental health conditions are leading causes of work interference and disability.[16–18] Costs related to health care, workers' compensation (WC) claims, and productivity are also higher for workers with chronic conditions.[8,11,15,19,20] For example, Colorado WC claim costs were $12,074 on average for workers with diabetes versus $3488 for workers without diabetes, and $6427 on average for workers with arthritis versus $3458 for workers without arthritis.[8] Nationally, accumulated burdens are massive, at over 2.5 billion annual days of work/productivity loss due to chronic conditions.[21] National annual indirect costs of rheumatoid arthritis-related absenteeism alone were estimated at $252 million.[22]

Historically, occupational safety and health (OSH) research has focused on chronic conditions caused by work (e.g., carpal tunnel syndrome and occupational lung disease), affecting about 7.5% of US workers.[23] More recently, the OSH field has broadened its focus to include all chronic conditions, affecting the health and well-being of over half the workforce.[24,25] Chronic conditions, regardless of causation, are included in the NIOSH Total Worker Health® paradigm.[24,26]

Measurement of chronic conditions is important for many occupational health research projects, either as the study focus, or to adjust for comorbidity burden. There are significant knowledge gaps regarding the importance of comorbidity adjustment when studying worker outcomes. However, chronic conditions have been challenging to study or to adjust for when relying on the administrative WC databases often used to study worker outcomes; WC databases are not designed to comprehensively track all chronic conditions. WC often excludes payment for such conditions unless deemed relevant to treatment or recovery (state rules vary), and chronic condition diagnosis codes may not always be included in WC billing. Because chronic conditions unrelated to a specific work injury/illness may not be billed to or reimbursed by WC, they are likely underrepresented in WC data, to an unknown degree. Consequently, confidence in the validity of comorbidity measures based on WC data is limited.

There is a pressing need for a chronic condition/comorbidity instrument validated for use with WC-based data. Comorbidity adjustment typically involves tools such as the Elixhauser Index or the Charlson Comorbidity Index.[27–29] These indices use International Classification of Diseases (ICD) diagnosis codes to identify conditions that predict mortality and hospitalization-related outcomes (e.g., length of stay, readmission, and costs), and have been well-validated for these purposes.[30–33] Deriving comorbidity measures from administrative data is advantageous because it allows for efficient large-scale research. However, selecting a comorbidity index appropriate to the data source, setting, population, and outcome of interest is important.[31] WC-based research usually focuses on return-to-work outcomes, for which few comorbidity indices are well-validated.

The Functional Comorbidity Index (FCI) is a unique comorbidity measure that is particularly well-suited for working populations and occupational health/worker outcome research, because it was developed to predict functional outcomes in community-based adult populations.[34] The standard FCI is an additive index of 18 chronic health conditions. Certain chronic conditions are strong predictors of work injury or work disability—some are variably included in other comorbidity indices (e.g., depression, diabetes, heart disease, obesity), but others are included only in the FCI (e.g., anxiety, asthma, chronic back pain, osteoarthritis, and vision/hearing impairments).[9,16–18,35–37] The FCI was first developed as an interview instrument[34] and was also validated as a chart review instrument.[38] More recently, the FCI has been validated using several diagnosis code lexicons contained in administrative/billing data,[39–42] and has been successfully used to predict 12-month outcomes (e.g., functional limitation, quality-of-life, and healthcare utilization) among older adult outpatients with back pain, with explanatory power comparable to the Charlson and Elixhauser indices.[43,44] Our research team previously produced compatible ICD-9-CM and ICD-10-CM diagnosis code lists for the FCI, to facilitate research spanning the lexicon transition.[41]

Several recent studies have shown promising utility for a WC-based FCI, despite limited validity data. For example, in a pair of Washington State WC-based studies by Sears et al.,[14,45] a higher FCI score was significantly associated with increased work interruptions and gaps, though not with delays in first return to work, nor with reinjury. Marcum et al.[13] found that injured workers with multimorbidity had significantly higher odds of not working, as well as poorer hours and earnings recovery, compared to those with no comorbidities.[13] In all three studies, the WC-based FCI was used to control confounding across groups, and the FCI significantly differed across the groups being compared (i.e., impairment level and injury type). Notably, only 7% had any FCI condition when using billing data for the first encounter,[14,45] versus 26%–43% when using all encounters.[13]

Despite strong face validity, the FCI has seldom been used in WC-based occupational health/worker outcome studies, and there has been no validation of the FCI specifically for use with WC data. Lack of knowledge of the degree of FCI under-ascertainment when using WC data could affect the accuracy of conclusions about the prevalence of chronic conditions among workers. Further, it is unclear whether using the FCI in WC-based studies is useful for partial comorbidity adjustment. There may be unidirectional misclassification and bias toward the null, or it might actually be harmful, by introducing bias via systematically differential missing or invalid diagnoses. In this study, we used WC administrative data linked to secondary data from a large prospective longitudinal survey of injured workers in Ohio and Washington State to address three aims. First, we assessed three alternative WC-based data sources for constructing the WC-based FCI: all bills (paid or unpaid), allowed bills (paid only), and accepted conditions (diagnoses accepted for payment related to the WC claim). Second, we assessed the validity of using WC-based diagnosis codes for identifying individual chronic conditions and constructing a WC-based FCI, compared to using an FCI constructed using self-reported conditions from survey data. Third, we assessed the WC-based FCI with regard to association with work outcomes and utility for control of confounding by comorbidity burden across states, compared to the survey-based FCI.

2 | METHODS

2.1 | Study population and data sources

2.1.1 | Study setting

WC coverage includes medical treatment and partial wage replacement (time-loss compensation) for workers who incur a work-related injury/illness. Workers with an accepted WC claim may be eligible for time-loss compensation after seven lost work days in Ohio and three in Washington State. Ohio and Washington are the largest of four states with an exclusive state fund (no private WC insurers), making them particularly well-suited to population-based research.[46,47] Approximately 60% of Ohio workers and over two thirds of Washington workers are covered by a state fund, administered by the Ohio Bureau of Workers' Compensation and the Washington State Department of Labor and Industries, respectively.

2.1.2 | Washington and Ohio Workers Study

The Washington and Ohio Workers (WOW) Study was funded by the Patient-Centered Outcomes Research Institute (PCORI) [UOP-2017C2-8509, PI: Franklin]. To compare the impact of opioid review programs in Ohio and Washington, the WOW Study included a prospective longitudinal survey of injured workers in both states, linked to WC claims and billing data from each state. The WOW Study complied with PCORI's stringent methodological standards.[48] The survey included injured workers in Ohio or Washington who (1) filed a state fund claim, (2) received an opioid prescription within 6 weeks of injury, and (3) could be interviewed in English or Spanish. The opioid criterion was based on paid WC pharmacy bills; workers reporting they did not fill or take their opioid prescription (8% for Ohio, 12% for Washington) were not excluded. Survey exclusion criteria were: (1) cancer at baseline (other than non-melanoma skin cancer), or (2) younger than 18 years old when injured. If an injured worker had more than one eligible claim during the study timeframe, the first eligible claim was included, and later claims for the same worker were excluded from baseline survey samples. Computer-assisted telephone interviews were conducted by the University of Washington (UW) Survey Research Division—baseline interviews approximately 6 weeks after work-related injury, and outcome interviews at 6 and 12 months. Survey questions included sociodemographics, chronic conditions (including the FCI), opioid use, work status, disability, function, health status, and quality of life. Baseline interviews began in Fall 2019 and ended in Fall 2021; 3730 were completed. The adjusted response rate using American Association for Public Opinion Research standard definitions (Response Rate 4).[49] was 53% for the baseline survey, and 88% for the 6-month survey. These rates are on the high end for WC-related surveys.[50–54] Further survey details can be found in the study protocol posted on clinicaltrials.gov.[55] All survey participants gave informed consent. This study was approved by the University of Washington Institutional Review Board.

2.1.3 | Study sample

All eligible workers with completed WOW Study baseline and 6-month follow-up interviews were included. This provided a study sample of 3351 injured workers (512 in Ohio and 2839 in Washington). Dates of work-related injury for this sample spanned June 16, 2019, through September 2, 2021.

2.2 | Functional Comorbidity Index

This study compares FCI data based on two sources—self-reported survey data and WC administrative data. Each version of the FCI was calculated as an additive (unweighted) index of 18 chronic health conditions. The self-reported FCI was based on the WOW baseline survey (conducted approximately 6 weeks after injury) that asked, for each of the 18 conditions, "During the past year, have you been affected by, diagnosed with, or treated for any of the following conditions?" Three alternative versions of the WC-based FCI were constructed for comparison to the self-reported FCI, using three different sources of WC administrative data and the ICD-10-CM diagnosis code-based definitions developed and published in a previous study[41]: (1) all professional/facility bills (paid or unpaid), (2) allowed professional/facility bills (paid only), and (3) accepted conditions (a cumulative list of diagnoses deemed by the WC agency as being related to the WC claim and thus accepted for WC coverage and payment; this list is distinct from billing data). Each data source was restricted to data generated during the 6-week period after injury. All three data sources contained ICD-10-CM diagnosis codes, and conditions were identified per our previously published FCI diagnosis list.[41]

2.3 | Outcome measures

To validate the WC-based FCI for the work-related administrative outcome most often used in WC-based research, the primary outcome was time-loss compensation (compensation for inability to work due to the work injury). For each worker, time-loss compensation status was assessed at 6 months after injury (binary; 0 = no, 1 = yes). A survey-based work status variable was also constructed for comparison, based on response to the 6-month outcome survey question, “During the past week have you worked for pay?” Survey responses were recoded to reflect the same conceptual direction as the time loss variable (binary; 0 = worked in the past week, 1 = did not work in the past week).

2.4 | Data analysis

All analyses were conducted at the individual worker level, stratified by state. Data analyses were conducted using Stata/MP Parallel Edition 17.0 for Windows (StataCorp).[56]

We calculated the observed prevalence (sample frequencies) for each of the 18 FCI conditions by state and by data source (i.e., survey, all bills, allowed bills, and accepted conditions). For each condition, we calculated concordance using Cohen's kappa[57]; Landis and Koch's guidelines were used to assess the results.[58] We also calculated sensitivity, specificity, and area under the receiver operating curve (AUC), comparing identification via WC administrative data to self-reported baseline survey data (treated as the reference standard).[59] Self-reported chronic conditions have been found reasonably accurate when assessed using medical records as the gold standard.[60] Though imperfect, self-report over a 12-month recall period is a reasonable reference standard for the FCI conditions, all of which have been shown to interfere with work/function. Evidence suggests higher validity of self-report for conditions that are more directly evident to the respondent.[60] AUC has the advantage of summarizing sensitivity and specificity into a single number, and is useful when it is desirable to weight sensitivity and specificity equally.[61] To evaluate AUC, we used qualitative guidelines based on recommendations by Hosmer and Lemeshow.[62] We also reported sensitivity and specificity estimates, as there are settings where maximizing one or the other is useful. For example, if one wished to identify a select group of workers with evidence of a specific comorbidity, maximizing specificity might be more important than sensitivity. We do not report positive and negative predictive values, as these measures vary with prevalence.[63]

For each worker, we calculated a separate FCI from each data source. We then calculated summary distributional statistics for the FCI by state and data source. We assessed predictive validity via assessing association with work outcomes using a series of logistic regression models with robust variance estimates. Each model contained one of the FCI versions, gender, age category, a binary flag for interview timing (pre-post March 2020; the survey spanned more than 2 years, including COVID-19 onset), and one of the two binary work outcomes. AUC was also reported for each model.

Finally, we assessed survey-based and WC-based FCI versions with regard to utility for control of confounding by comorbidity burden across states. This was of particular interest, given probable differences across state WC programs in rules and practices over coverage of comorbid conditions that could affect comorbidity ascertainment via administrative data, as well as cross-state differences in WC administrative data generation and management. For example, Ohio data had only two diagnosis fields available for inpatient and outpatient facility bills, whereas Washington had up to 32. On the other hand, Ohio had five diagnosis fields available for professional bills, whereas Washington had only four. Therefore, we constructed one additional FCI version for this assessment—a state-aligned allowed-bills version, in which the number of available diagnosis data fields was trimmed to the same number for each state before FCI calculation; that is, a maximum of two diagnosis fields for inpatient and outpatient facility bills, and a maximum of four diagnosis fields for professional bills. This was done in hopes of improving FCI comparability across the two states, given the discrepancies in the number of diagnoses available. The base models for this assessment were logistic regression models with robust variance estimates; each base model contained gender, age category, and a binary flag for interview timing as covariates and predicted one of the two binary work outcomes. In addition, for this assessment, a variable for state was added (Ohio coded as 0, Washington coded as 1) and treated as the predictor of interest. Then, in turn, one of the three FCI versions (survey, allowed bills, state-aligned allowed bills) was added to each base model. We used the change-in-estimates method,[64] to compare the impact on the associations between state and each of the two work outcomes; the reported percent change reflects the relative change in the Washington effect estimate moving from the base model to a model including the indicated FCI version.

3 | RESULTS

Sample descriptive statistics for each state are presented in Table 1. The Ohio sample consisted of 512 workers. Six months after injury, 18.8% of the Ohio sample received time-loss compensation, while

TABLE 1 Sample characteristics by state.

Characteristic	Ohio (*N* = 512) % (*n*)	Washington (*N* = 2839) % (*n*)
Women	28.1% (144)	24.6% (699)
Age		
18–24	7.2% (37)	9.6% (273)
25–34	18.0% (92)	24.5% (695)
35–44	24.0% (123)	24.2% (686)
45–54	21.3% (109)	22.5% (638)
55–64	24.2% (124)	16.3% (464)
65+	5.3% (27)	2.9% (83)
COVID-19 era injury (on or after 3/1/2020)	52.5% (269)	40.9% (1162)
Work outcome (6 months after injury)		
On time loss (WC data)	18.8% (96)	15.1% (428)
Not working past week (survey data)	41.8% (178)	32.4% (781)

Abbreviation: WC, workers' compensation.

TABLE 2 FCI condition prevalence 6 weeks after injury using self-reported survey data and WC administrative data.

FCI condition	Survey			All bills		Allowed bills		Accepted conditions	
	Sample *N*[a]	*n* Cases	Prevalence	*n* Cases	Prevalence	*n* Cases	Prevalence	*n* Cases	Prevalence
Ohio (*N* = 512)									
Arthritis	506	86	17.0%	10	2.0%	10	2.0%	0	0.0%
Osteoporosis	507	10	2.0%	2	0.4%	2	0.4%	0	0.0%
Asthma	511	51	10.0%	2	0.4%	2	0.4%	0	0.0%
Chronic respiratory disease	509	15	3.0%	0	0.0%	0	0.0%	0	0.0%
Angina	510	12	2.4%	0	0.0%	0	0.0%	0	0.0%
Heart disease	509	9	1.8%	1	0.2%	1	0.2%	0	0.0%
Myocardial infarction	510	3	0.6%	0	0.0%	0	0.0%	0	0.0%
Neurological disease	510	8	1.6%	2	0.4%	2	0.4%	0	0.0%
Stroke or TIA	510	2	0.4%	1	0.2%	1	0.2%	0	0.0%
Peripheral vascular disease	505	2	0.4%	0	0.0%	0	0.0%	0	0.0%
Diabetes (type I or II)	508	53	10.4%	6	1.2%	6	1.2%	0	0.0%
Upper gastrointestinal disease	511	57	11.2%	1	0.2%	1	0.2%	0	0.0%
Depression	508	81	15.9%	1	0.2%	1	0.2%	0	0.0%
Anxiety or panic disorder	508	99	19.5%	2	0.4%	2	0.4%	0	0.0%
Visual impairment	510	49	9.6%	0	0.0%	0	0.0%	0	0.0%
Hearing impairment	510	18	3.5%	0	0.0%	0	0.0%	0	0.0%
Back disease	510	69	13.5%	18	3.5%	18	3.5%	4	0.8%
Obesity (body mass index ≥ 30)	495	81	16.4%	3	0.6%	3	0.6%	0	0.0%
Washington (*N* = 2839)									
Arthritis	2818	319	11.3%	106	3.7%	105	3.7%	22	0.8%
Osteoporosis	2822	36	1.3%	6	0.2%	6	0.2%	0	0.0%
Asthma	2833	217	7.7%	84	3.0%	82	2.9%	0	0.0%
Chronic respiratory disease	2835	53	1.9%	23	0.8%	22	0.8%	0	0.0%
Angina	2831	67	2.4%	0	0.0%	0	0.0%	0	0.0%
Heart disease	2834	36	1.3%	24	0.9%	24	0.9%	0	0.0%
Myocardial infarction	2838	17	0.6%	17	0.6%	17	0.6%	0	0.0%
Neurological disease	2836	30	1.1%	14	0.5%	13	0.5%	2	0.1%
Stroke or TIA	2834	16	0.6%	10	0.4%	7	0.3%	0	0.0%
Peripheral vascular disease	2822	9	0.3%	2	0.1%	2	0.1%	0	0.0%
Diabetes (type I or II)	2827	217	7.7%	130	4.6%	128	4.5%	0	0.0%
Upper gastrointestinal disease	2830	290	10.3%	58	2.0%	57	2.0%	0	0.0%
Depression	2830	380	13.4%	57	2.0%	56	2.0%	11	0.4%
Anxiety or panic disorder	2824	508	18.0%	77	2.7%	74	2.6%	14	0.5%
Visual impairment	2828	242	8.6%	2	0.1%	2	0.1%	0	0.0%
Hearing impairment	2826	126	4.5%	11	0.4%	11	0.4%	4	0.1%
Back disease	2816	307	10.9%	215	7.6%	210	7.4%	62	2.2%
Obesity (body mass index ≥ 30)	2722	371	13.6%	133	4.7%	129	4.5%	1	0.0%

Abbreviations: FCI, Functional Comorbidity Index; TIA, transient ischemic attack; WC, workers' compensation.

[a]There was a separate interview question for each comorbidity; hence, missing data varied slightly (i.e., don't know, decline to answer).

TABLE 3 FCI condition concordance, sensitivity, specificity, and area under the receiver operating curve (AUC), comparing WC administrative data within 6 weeks after injury (allowed bills) to self-reported 6-week survey data.

FCI condition	Ohio (*N* = 512): Allowed bills				Washington (*N* = 2839): Allowed bills			
	Kappa[a]	Sensitivity	Specificity	AUC[b]	Kappa[a]	Sensitivity	Specificity	AUC[b]
Arthritis	0.007	2.3%	98.1%	0.502	0.151	13.2%	97.5%	0.553
Osteoporosis	−0.007	0.0%	99.6%	0.498	0.044	2.8%	99.8%	0.513
Asthma	0.030	2.0%	99.8%	0.509	0.298	22.6%	98.7%	0.607
Chronic respiratory disease	0.000	n/c	n/c	n/c	0.232	17.0%	99.5%	0.583
Angina	0.000	n/c	n/c	n/c	0.000	n/c	n/c	n/c
Heart disease	−0.004	0.0%	99.8%	0.499	0.226	19.4%	99.4%	0.594
Myocardial infarction	0.000	n/c	n/c	n/c	0.172	17.7%	99.5%	0.586
Neurological disease	0.195	12.5%	99.8%	0.562	0.228	16.7%	99.7%	0.582
Stroke or TIA	−0.003	0.0%	99.8%	0.499	−0.003	0.0%	99.8%	0.499
Peripheral vascular disease	0.000	n/c	n/c	n/c	0.181	11.1%	100.0%	0.555
Diabetes (type I or II)	0.186	11.3%	100.0%	0.557	0.569	47.0%	99.0%	0.730
Upper gastrointestinal disease	0.031	1.8%	100.0%	0.509	0.120	9.0%	98.8%	0.539
Depression	−0.004	0.0%	99.8%	0.499	0.093	7.1%	98.8%	0.530
Anxiety or panic disorder	0.012	1.0%	99.8%	0.504	0.115	8.9%	98.8%	0.538
Visual impairment	0.000	n/c	n/c	n/c	0.007	0.4%	100.0%	0.502
Hearing impairment	0.000	n/c	n/c	n/c	0.066	4.0%	99.8%	0.519
Back disease	0.087	8.7%	97.3%	0.530	0.170	20.2%	94.3%	0.573
Obesity (body mass index ≥ 30)	−0.012	0.0%	99.3%	0.496	0.165	14.8%	97.1%	0.559

Abbreviations: AUC, area under the receiver operating curve; FCI, Functional Comorbidity Index; n/c, no cases; TIA, transient ischemic attack; WC, workers' compensation.

[a]Kappa values < 0 can be interpreted as indicating no agreement, 0–0.20 as slight, 0.21–0.40 as fair, 0.41–0.60 as moderate, 0.61–0.80 as substantial, and 0.81–1 as almost perfect agreement.[59]

[b]AUC values can be interpreted as: (a) if AUC = 0.5, the test has no discrimination, (b) 0.5 < AUC < 0.7, poor discrimination, (c) 0.7 ≤ AUC < 0.8, acceptable discrimination, (d) 0.8 ≤ AUC < 0.9, excellent discrimination, and (e) AUC ≥ 0.9, outstanding discrimination.[63]

TABLE 4 FCI distributions by state and FCI data source (survey or allowed bills).

FCI	Ohio (*N* = 512)		Washington (*N* = 2839)	
	Survey	Allowed bills	Survey	Allowed bills
Mean	1.38	0.10	1.14	0.33
SD	1.69	0.34	1.54	0.70
Median	1	0	1	0
Minimum	0	0	0	0
Maximum	9	3	14	6
Percent (*n*) with any FCI condition	57.6% (295)	8.4% (43)	52.3% (1486)	24.0% (682)

Abbreviation: FCI, Functional Comorbidity Index.

41.8% reported not working during the past week. The Washington sample consisted of 2,839 workers. Six months after injury, 15.1% of the Washington sample received time-loss compensation, while 32.4% reported not working during the past week.

Table 2 presents the observed prevalence for each of the 18 FCI conditions by state and by data source (i.e., survey, all bills, allowed bills, and accepted conditions). Observed prevalence was much lower using administrative data compared to self-reported survey data—for all conditions, and particularly for Ohio. Using all bills compared to allowed (paid) bills resulted in negligible differences in observed prevalence, but also increased the risk of including billing errors. Using accepted conditions resulted in identifying vanishingly few comorbidities. We therefore focused all further administrative data analyses on allowed bills, using survey data as the reference standard where appropriate.

Table 3 presents concordance (Cohen's kappa), sensitivity, specificity, and AUC, comparing identification via WC administrative data to self-reported baseline survey data (treated as the reference standard). Using Landis and Koch's guidelines for assessing concordance,[58] there was no agreement or only slight agreement between self-report and allowed bills for all 18 conditions in Ohio. In Washington, the same was true for most conditions, but four conditions exhibited fair agreement (asthma, chronic respiratory

TABLE 5 Predictive validity logistic regression models,[a] comparing allowed bill-based FCI to survey-based FCI by state.

	Survey			Allowed bills		
Work outcome by state	OR (95% CI)	*P*	AUC[b]	OR (95% CI)	*P*	AUC[b]
Ohio						
On time loss (WC data; *N* = 512)	1.054 (0.916–1.213)	0.46	0.663	1.580 (0.883–2.826)	0.12	0.671
Not working past week (Survey data; *N* = 426)	1.003 (0.889–1.131)	0.96	0.569	1.861 (1.095–3.162)	0.02	0.568
Washington						
On time loss (WC data; *N* = 2839)	1.064 (0.994–1.139)	0.07	0.575	1.329 (1.172–1.508)	<0.001	0.591
Not working past week (Survey data; *N* = 2413)	1.050 (0.993–1.110)	0.09	0.568	1.110 (0.987–1.248)	0.08	0.571

Abbreviations: AUC, area under the receiver operating curve; CI, confidence interval; FCI, Functional Comorbidity Index; OR, odds ratio; WC, workers' compensation.

[a]Each model contained one of the FCI versions, gender, age category, a binary flag for interview timing (pre-post March 2020; the survey spanned more than 2 years, including COVID-19 onset), and one of the two binary work outcomes.

[b]AUC values can be interpreted as: (a) if AUC = 0.5, the test has no discrimination, (b) 0.5 < AUC < 0.7, poor discrimination, (c) 0.7 ≤ AUC < 0.8, acceptable discrimination, (d) 0.8 ≤ AUC < 0.9, excellent discrimination, and (e) AUC ≥ 0.9, outstanding discrimination.[63]

TABLE 6 Confounding assessment using three FCI versions (survey, allowed bills, state-aligned allowed bills) and state as the predictor of work outcomes (Washington = 1 vs. Ohio = 0).

Work outcome	Base model[a]	Models with one of three FCI versions added					
		Survey		Allowed bills		State-aligned allowed bills[b]	
	OR (95% CI)	OR (95% CI)	% Δ[c]	OR (95% CI)	% Δ[c]	OR (95% CI)	% Δ[c]
On time loss[d]	0.823 (0.644–1.052)	0.830 (0.649–1.062)	0.85	0.749 (0.584–0.961)	8.95	0.766 (0.598–0.982)	6.87
Not working past week[e]	0.686 (0.554–0.850)	0.689 (0.556–.854)	0.44	0.661 (0.532–0.820)	3.70	0.667 (0.537–0.827)	2.82

CI, confidence interval; FCI, Functional Comorbidity Index; OR, odds ratio; % Δ, percent change; WC, workers' compensation.

[a]Each logistic regression base model contained gender, age category, and a binary flag for interview timing as covariates, and predicted one of the two binary work outcomes. In addition, a variable for state was added (Ohio coded as 0, Washington coded as 1), and treated as the predictor of interest. Then, in turn, one of the three FCI versions was added to each base model.

[b]Data were trimmed to same number of diagnosis fields for each state before calculating allowed bill-based FCI.

[c]Percent change reflects the relative change in the Washington effect estimate moving from the base model to a model including the indicated FCI version.

[d]WC data: *N* = 3351 (Washington *n* = 2839; Ohio *n* = 512).

[e]Survey data: *N* = 2839 (Washington *n* = 2413; Ohio *n* = 426).

disease, heart disease, and neurological disease), and diabetes exhibited moderate agreement. Using Hosmer and Lemeshow's guidelines for assessing AUC,[62] Ohio allowed bills provided poor to no discrimination for whether any of the 18 FCI conditions were present on self-report. The same was true for Washington, with the notable exception that allowed bills provided substantial discrimination (AUC = 0.730) for diabetes; nevertheless, allowed bill-based sensitivity for diabetes was only 47.0%. In other words, using WC billing data (allowed bills) to identify workers with diabetes diagnoses, we were able to identify only 47% of the workers who had self-identified in the survey as having diabetes.

Table 4 presents the summary of distributional statistics for the survey-based and allowed bill-based FCIs for each state. The survey-based FCI was markedly higher than the WC-based FCI in both states. In Ohio, 57.6% of workers self-reported at least one of the 18 FCI conditions, while allowed bills identified only 8.4% of workers with any of those conditions. In Washington, 52.3% of workers self-reported at least one of the FCI conditions, while allowed bills identified 24.0%. Notably, although the survey-based FCI suggested more comorbidity in the Ohio sample, the allowed bill-based FCI suggested more comorbidity in the Washington sample.

Table 5 presents the findings of the logistic regression models used to assess the association between the FCI versions (survey-based and allowed bill-based) and work outcomes. The survey-based FCI did not have significant predictive validity for either work-related outcome; however, a weak nonsignificant association of higher FCI with poorer work outcomes trended in the same direction (odds ratio above 1) for both outcomes in both states. In general, and in both states, there were larger effect sizes and stronger associations for the allowed bill-based FCIs compared to the survey-based FCIs. Nevertheless, AUC estimates indicated poor outcome prediction by all models.

Finally, we assessed survey-based and WC-based FCI versions with regard to utility for control of confounding by comorbidity burden across states. The percent change estimates reported in Table 6 reflect the relative change in the effect estimates (associations between being a Washington vs. Ohio worker and work outcomes), moving from a base model that did not include an FCI version to a model including the indicated FCI version.

For both work outcomes, adding the survey version of the FCI to the base model moved the state effect estimates very slightly toward the null, with under 1% change. However, substituting the allowed-bills FCI version had a fairly dramatic impact on the state effect estimates for the WC-based time loss outcome (8.95% change)—importantly, this moved the estimate away from the null. This was also true for the self-reported work outcome, though less dramatic (3.70% change). Substituting the state-aligned allowed-bills FCI resulted in a similar pattern, though the percent change was somewhat smaller (6.87% change for the WC-based work outcome and 2.82% change for the self-reported work outcome). The survey-based FCI should be comparably accurate across states; hence, these findings suggest that using a WC-based FCI across states, even after constructing it to account for differences in the number of diagnosis data fields across states, may actually introduce confounding rather than adjust for it.

4 | DISCUSSION

In this study, we assessed the FCI as an instrument to measure comorbidity burden in the context of WC administrative data, using survey data as the reference standard. Of the three administrative data sources we assessed (all bills, allowed bills, and accepted conditions), we preferred the FCI calculated from allowed (paid) bills based on the analyses presented in Table 2 as well as face validity. Using all bills rather than allowed (paid) bills resulted in negligible ascertainment differences and may increase the risk of including billing errors. Using accepted conditions resulted in minimal comorbidity ascertainment; to be included as an accepted condition, the WC agency must have deemed a diagnosis to be related to treatment for—or recovery from—the work-related injury/illness.

Observed prevalence for the 18 FCI conditions was much lower using WC administrative data compared to self-report, particularly in Ohio. In both states, there was generally poor agreement between self-report and allowed bills, with a few exceptions in Washington (Table 3). For most conditions, WC billing data exhibited very high specificity, but very low sensitivity. Over half of workers in both states self-reported at least one of the FCI conditions, while allowed bills identified only 8.4% in Ohio and 24.0% in Washington. The WC-based FCI may be useful for identifying specific subsets of workers with particular chronic conditions, but less useful for assessing chronic condition prevalence among injured workers, except perhaps as a lower-bound estimate. We also found that the FCI was only weakly associated with work-related outcomes, whether those outcomes were based on self-report or administrative data (Table 5). In general, and in both states, there were larger effect sizes and stronger associations for the allowed bill-based FCIs compared to the survey-based FCIs. This counter-intuitive finding may be an artifact of preferentially adding billing diagnoses for conditions already accepted or expected to affect work outcomes for a particular worker. Nevertheless, certain studies may call for control of confounding by comorbidity, and the WC-based FCI may be of use for that purpose within the context of a single state.

On the other hand, our analyses raised red flags about using a WC administrative data-based FCI in the context of multiple states. Notably, although the survey-based FCI suggested more comorbidity in the Ohio sample, the allowed bill-based FCI suggested more comorbidity in the Washington sample (Table 4). This observation underpinned concerns about using the FCI in cross-state analyses, and motivated the confounding assessment presented in Table 6. In that assessment, we found evidence that using a WC-based FCI across states, even after tailoring its construction to account for differences in the number of diagnosis data fields across states, may actually introduce additional confounding rather than adjust for it. We therefore strongly caution against using an FCI in studies involving administrative data from more than one state, at least in the absence of further detailed analysis using a reliable reference standard from all states involved. Although the low sensitivity of WC billing data for identification of chronic conditions may sometimes be acceptable in the context of a single state, cross-state differences in rules and practices for coverage of comorbid conditions, as well as cross-state differences in WC administrative data generation and management, may result in ascertainment differences that render cross-state comparison untenable. We found the differences between the WC-based FCI in Ohio and Washington to be substantial. Although we cannot generalize our findings to states beyond Ohio and Washington, we do believe that general caution toward cross-state FCI comparisons is warranted. In particular, both Ohio and Washington have exclusive state funds (explained in Section 2.1.1); states that have a combination of private WC insurers and state funds might exhibit even larger differences in FCI performance.

This secondary analysis leveraged WC administrative data linked to survey data that was available from a prospective cohort study, providing a reference standard for our assessment of the WC-based FCI. For both Ohio and Washington, samples were drawn from a population-based exclusive state fund. Population-based generalizability was limited by a core inclusion criterion for the parent study—the presence of at least one WC paid bill for an opioid prescription in the first 6 weeks after injury. However, the 12% reporting they did not actually take opioids were not excluded from this study. One concern related to this inclusion criterion was the prospect of differential inclusion by comorbidity burden. In other words, if workers with opioid prescriptions were more likely than other injured workers to have comorbidities, our study sample might be expected to have a heavier comorbidity burden than the general WC population. However, the self-reported comorbidity prevalences observed in this study were not particularly high. Further, WC payment for an opioid prescription would almost certainly reflect treatment related to the work injury/illness (vs. treatment related to a pre-existing comorbidity), reducing the likelihood of differential inclusion by comorbidity prevalence.

5 | CONCLUSIONS

In this study, we assessed the FCI as an instrument to measure comorbidity burden in the context of WC administrative data. As expected, the observed prevalence for each of the 18 FCI conditions was much lower using WC administrative data than self-reporting. When limited to WC administrative data, the previously validated diagnosis code lists for calculating the FCI may be useful for identifying specific subsets of workers with particular chronic conditions, but less useful for assessing chronic condition prevalence among injured workers. As an illustration, the FCI diagnosis code categories could be used with WC administrative data to identify a highly specific subset of injured workers with depression, for example, and a study of outcomes among workers with depression could be conducted with a reasonable degree of confidence in the inclusion criteria. However, constructing a category of injured workers without depression (for use as a comparator to those with depression) would likely be subject to substantial misclassification. Further, the low sensitivities of all FCI diagnosis code categories, as documented by this study, do not support calculating the prevalence of depression (or any other FCI condition) among injured workers using WC administrative data, except as a lower-bound estimate. The WC-based FCI was only weakly associated with work-related outcomes. Nevertheless, certain studies may call for control of confounding by comorbidity, and the WC-based FCI may be useful for that purpose within the context of a single state. However, the differences between the WC-based FCI in Ohio and Washington were substantial. Using the WC-based FCI cross-state appeared to introduce additional confounding by comorbidity burden, rather than mitigating it. We therefore strongly advise caution—to include undertaking state-specific analyses using a reliable reference standard—before using a WC-based FCI in studies involving administrative data from more than one state.

AUTHOR CONTRIBUTIONS

Jeanne M. Sears, Sean D. Rundell, and Sheilah Hogg-Johnson participated in the conception and design of the work; Jeanne M. Sears, Deborah Fulton-Kehoe, and Gary M. Franklin participated in the acquisition of data; Jeanne M. Sears conducted the analysis; and Jeanne M. Sears drafted the work. All five authors participated in the interpretation of data and revising the work critically for important intellectual content, provided final approval of the version to be published, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DISCLOSURE BY AJIM EDITOR OF RECORD

John Meyer declares that he has no conflict of interest in the review and publication decision regarding this article.

DATA AVAILABILITY STATEMENT

Research data are not shared.

ETHICS APPROVAL AND INFORMED CONSENT

All survey participants gave informed consent. This study was approved by the University of Washington Institutional Review Board.

DISCLAIMER

The findings and conclusions in this report are solely the responsibility of the authors and do not necessarily represent the official views of the National Institute for Occupational Safety and Health.

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