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Using Job-Title-Based Physical Exposures From O*NET in an Epidemiological Study of Carpal Tunnel Syndrome

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Objective: We studied associations between job-title-based measures of force and repetition and incident carpal tunnel syndrome (CTS).

Background: Job exposure matrices (JEMs) are not commonly used in studies of work-related upper-extremity disorders.

Method: We enrolled newly hired workers in a prospective cohort study. We assigned a Standard Occupational Classification (SOC) code to each job held and extracted physical work exposure variables from the Occupational Information Network (O*NET). CTS case definition required both characteristic symptoms and abnormal median nerve conduction.

Results: Of 1,107 workers, 751 (67.8%) completed follow-up evaluations. A total of 31 respondents (4.4%) developed CTS during an average of 3.3 years of follow-up. Repetitive motion, static strength, and dynamic strength from the most recent job held were all significant predictors of CTS when included individually as physical exposures in models adjusting for age, gender, and BMI. Similar results were found using time-weighted exposure across all jobs held during the study. Repetitive motion, static strength, and dynamic strength were correlated, precluding meaningful analysis of their independent effects.

Conclusion: This study found strong relationships between workplace physical exposures assessed via a JEM and CTS, after adjusting for age, gender, and BMI. Though job-title-based exposures are likely to result in significant exposure misclassification, they can be useful for large population studies where more precise exposure data are not available.

Application: JEMs can be used as a measure of workplace physical exposures for some studies of musculoskeletal disorders.

Keywords: carpal tunnel syndrome, job exposure matrix, O*NET, prospective cohort study, ergonomics

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INTRODUCTION

Assessment of workplace physical exposures is a critical aspect of research into work-related musculoskeletal disorders. Existing methods for exposure assessment all suffer from various limitations. Direct measurement of worker exposures and detailed observational assessments are precise but may misclassify exposures in jobs where exposures vary over a longer time than the period of job observation (Hansson et al., 2001; Mathiassen & Paquet, 2010). Direct measurement and observation are also time-consuming, potentially limiting the study of large cohorts of workers. Exposure questionnaires are easier to administer to large populations, but exposures are probably less precise than observation or direct measurement and are subject to recall or other information biases (Viikari-Juntura et al., 1996). Although prospectively obtained individual level data are considered the best estimates of exposure, these methods are difficult to apply in large cohort studies, and often cannot be applied to studies of existing data. The availability of large population data sets containing information on job title and musculoskeletal disease outcomes could prove to be valuable, particularly for relatively uncommon disorders such as carpal tunnel syndrome (CTS) and ulnar neuropathy, and for disorders such as osteoarthritis, where relevant exposures may be cumulative or have occurred years before disease recognition.

In the absence of individual level exposure data, job exposure matrices (JEMs) are used in occupational epidemiology research to estimate respondents' exposures to chemical and physical risk factors based on job titles, industry information, and population exposure data (Plato & Steineck, 1993). Although JEMs have been used in previous studies of work-related musculoskeletal disorders, including CTS, their use is not common. We used data on physical job demands from the Occupational Information Network (O*NET; https://onet.rti.org/) to construct a JEM in a large cohort study of CTS incidence. O*NET is a publicly available data set describing the physical and mental requirements of more than 800 occupations, defined based on Standard Occupational Classification (SOC). Job demand data in O*NET combine data from questionnaires of workers and professionals familiar with each job and ratings by job analysts. O*NET thus provides a means to link job titles with information about job exposures, enabling examination of exposure response relationships that might otherwise be infeasible due to missing or unavailable job exposure data (Cifuentes, Boyer, Lombardi, & Punnett, 2010).

CTS is the most common peripheral entrapment neuropathy, yet is still relatively uncommon, with a reported one-year cumulative incidence of 4.5% in industrial workers (Werner et al., 2005) and 7.5% in general manufacturing workers (Silverstein et al., 2010). The major work-related risk factors for CTS are forceful hand and repetitive hand movements (Barcenilla, March, Chen, & Sambrook, 2012; Bernard, 1997). Other exposures may also be relevant, including hand/wrist posture, hand vibration, and cold ambient temperature. Although CTS has been extensively studied in the past two decades, a number of limitations still exist in our understanding of the role that work exposures and their interactions with personal risk factors play in the etiology and natural history of CTS. Until recently there have been few large scale prospective studies of CTS that took into account personal risk factors and work-related exposures (Bonfiglioli et al., 2012).

The purpose of this study was to demonstrate the use of a JEM to study work-related exposures on the incidence of CTS in a large and heterogeneous cohort of workers.

METHOD

Respondent Recruitment

We analyzed data from the Predicting Carpal Tunnel Syndrome (PrediCTS) study, a prospective study of 1,107 newly hired workers enrolled between 2004 and 2006 from eight employers and three trade union apprenticeship programs in the metropolitan area of St. Louis, USA. Eligible respondents were at least 18 years of age, worked a minimum of 30 hours per week, and either were newly hired or had recently completed the probationary period for new employees. Respondents were excluded if they had a past diagnosis of CTS or other upper-extremity peripheral neuropathy, had a pacemaker or internal defibrillator, or were pregnant at the time of enrollment. At time of enrollment, workers were primarily employed as construction workers, technical or laboratory workers, clerical workers, or hospital service workers. The Washington University School of Medicine and the University of Michigan Institutional Review Boards approved this study, and all respondents provided written informed consent to participate. Respondents were compensated for participation.

Data Collection

All participants completed a physical examination of the upper extremities and bilateral nerve conduction studies of the hands and wrists at baseline and at follow-up 3 to 5 years later. Participants were asked to complete repeated self-administered questionnaires at baseline, at 6, 18, and 36 months following enrollment, and annually thereafter. The questionnaires sought information about personal demographics, the quality and location of upper-extremity symptoms, job title and other work information, and medical history. Respondents with hand symptoms drew the quality and location of their symptoms on a modified Katz hand diagram (Dale, Strickland, Symanzik, Franzblau, & Evanoff, 2008; Franzblau et al., 1994). Two research team members (an occupational physician and an occupational therapist) independently coded these hand diagrams to determine the presence of numbness, tingling, burning, or pain in one or more digits innervated by the median nerve. Disagreements in coding were resolved by consensus.

Physical examination and nerve conduction studies were performed by a research technician trained and monitored in a standard examination protocol. Physical examinations included sensory testing, provocative maneuvers of the arms and wrists, wrist anthropometrics, and weight and height. Nerve conduction studies used an automated nerve testing device, the NC-stat (NeuroMetrix Inc., Waltham, MA). Testing procedures followed the manufacturer's recommendations with sensor placement by anatomical landmarks. We measured both distal sensory and motor latencies of the median and ulnar nerves across the wrist for both hands, without external warming. The raw sensory latency values for the median and ulnar nerves were adjusted to a standard 14 centimeter length using the measured stimulus-response distance for each test. The skin temperature at the wrist was measured for each test, and conduction values were normalized to a temperature of 32° using manufacturer recommended correction values.

Health Outcome

Our CTS case definition required typical symptoms of CTS in one or more digits innervated by the median nerve and median neuropathy in the same hand. Symptoms were assessed via a screening question requiring recurrent or prolonged hand symptoms, by questions describing the quality of symptoms (numbness, tingling, burning, or pain), and by pain location assessed by a modified Katz hand diagram (palmar symptoms involving the distal digits 1, 2, or 3 not located only in joints). Median neuropathy was defined as a sensory latency > 3.5 ms or motor latency > 4.5 ms or a median-ulnar sensory latency difference of > 0.5 ms (Silverstein et al., 2010). Latency results that were unobtainable due to extremely prolonged latencies or very small amplitudes were also considered neuropathic. Respondents with unilateral or bilateral CTS were counted as a CTS case.

Job-Title-Based Exposures Derived From O*NET

On each survey, participants listed their current job title, company name, start date of job, and a description of related work exposures for the current or most recent job. Additional questions asked for the end date of previous jobs, average weekly work hours, and current employment status. All job titles and employers reported across repeated surveys were combined into a single data set with start and end dates of each job of each respondent. We independently assigned an SOC code (Version 2010) to each job title, using the job title selection feature provided by O*NET OnLine, a tool created for the U.S. Department of Labor by the National Center for O*NET Development (O*NET, U.S. Department of Labor/Employment and Training Administration, 2012b). All job titles were coded independently by two raters, with differences resolved by consensus.

Based on the SOC code assigned to each job, occupation-specific physical work exposure variables for each job held by each respondent were extracted from the O*NET 16.0 databases (O*NET, U.S. Department of Labor/Employment and Training Administration, 2012c). Six items that described physical exposures of hand force and repetition of the upper extremity were selected from three different O*NET databases (work activities, work context, and work abilities). The selected items were (a) handling and moving objects, (b) dynamic strength, (c) static strength, (d) wrist and finger speed, (e) time spent making repetitive movements, and (f) time spent using the hand to handle, control, or feel objects. Question formats for two exposures are shown in Figure 1 and illustrate two different types of questions. For time spent making repetitive motions, a 5-point ordinal scale is used ranging from *never* to *continually or almost continually*. This format is also used for time spent using the hand to handle, control, or feel objects. For static strength, two scales are used by O*NET. The first asks how important the physical attribute is to the current job; the second ranks the level of the exposure on a 7-point ordinal scale with descriptive verbal anchors. If the first scale is scored 1 for *not important*, the second question on level of exposure is skipped by the respondent and a value of 0 is assigned for this exposure; if scored as important, then a value is selected from the second 7-point ordinal scale. This scale format was also used for dynamic strength, handling and moving objects, and wrist and finger speed. Values contained in the O*NET databases are the mean value of scores for each item obtained from job incumbents, occupational experts, or occupational analysts.

For all respondents in our study, every job they held during the study was assigned an SOC

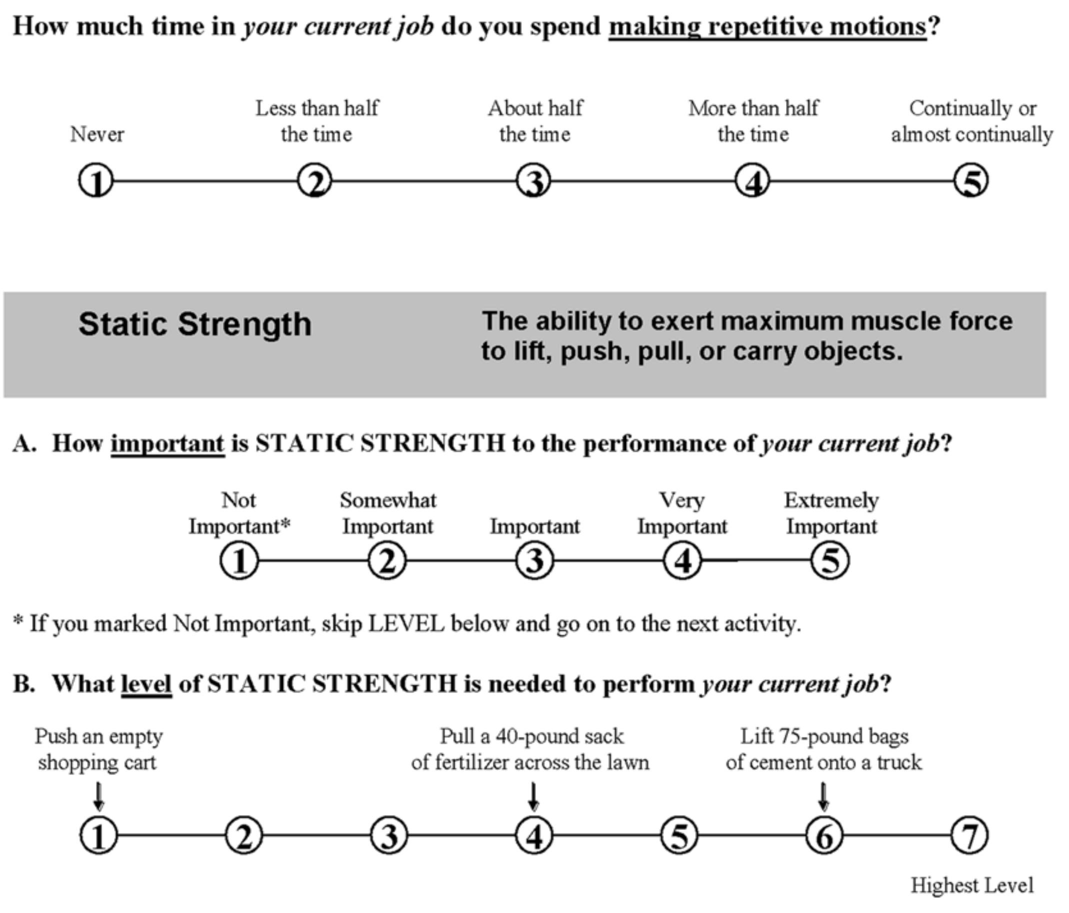

Figure 1. O*NET question format.

code, and for each exposure studied, the value given by O*NET was assigned to every job. Similar methods for using the O*NET databases have been described in previous publications (Cifuentes et al., 2010; Gardner, Landsittel, Nelson, & Pan, 2000; Gardner, Lombardi, Dale, Franzblau, & Evanoff, 2010).

Data Analysis

We used two different models of exposure over time. First, we used the exposures for the most recent job that was held a minimum of 6 months. Second, we used the employed time-weighted exposures, with each exposure weighted by the ratio of the length of time in that job over the sum of all employed time during the study period, excluding periods of unemployment.

We initially compared all personal and exposure variables to the CTS outcome to identify significant associations in univariate mixed logistic regression models. Exposure variables with an alpha level below .1 using both exposure definitions were retained for mixed multivariable models. Because exposure measures were at the level of the job whereas outcome measures were at the level of the individual worker, Cifuentes et al. (2010) recommended the use of hierarchical modeling or robust variance estimation techniques to account for the artificially reduced variance in O*NET data. We used a logistic regression mixed model with random intercepts grouped on job title, and a bias correction of the classical “sandwich” estimator suggested by Morel, Bokossa, and Neerchal. This estimator was chosen because it performs well at correcting the variance regardless of model misspecification, the number of clusters, or the distribution of the outcome (Morel, Bokossa, & Neerchal, 2003). The personal factors for age, gender, and body mass index (BMI) were retained as these are considered relevant for the health outcome. Diabetes and arthritis were not significant predictors in our cohort due to their low prevalence; these factors were not used in the final multivariable models.

We examined the distribution of the exposure variables to determine appropriate parameterizations in the regression models. The repetitive motion variable had an approximately normal distribution with a mean score of 3.6 ($SD = 0.6$). The static and dynamic strength variables showed nonnormal distributions and a nonlinear threshold relationship with CTS. Thus, dynamic strength was dichotomized, with the lowest category representing jobs where dynamic strength was rated as mostly or completely irrelevant to the job (mean score < 1). Approximately 68.4% of scores had a dynamic strength rating greater or equal to 1. For static strength, the cut point for dichotomization was a mean score < 2, resulting in 74.5% of scores being classified in the higher category.

To detect potential multicollinearity, we explored the relationships between exposures using correlations, *t* tests, or chi-square tests as appropriate. We ran separate multivariable regression models defined by most recent job and employed time-weighted. We ran sensitivity analysis to test the effect of recent periods of unemployment by restricting the analysis to respondents with recent jobs held within the past year, excluding those with long periods of unemployment. We also ran sensitivity analyses including diabetes and arthritis as risk factors, and analyses using 3 months instead of 6 as the minimum duration for a recent job. All analyses were conducted using SAS 9.3 (SAS Institute Inc., Cary, NC).

RESULTS

Demographics and Health Outcomes

Of the 1,107 workers characterized at baseline, 751 (67.8%) completed follow-up testing with physical examination and nerve conduction testing. Of these 751 respondents, 34 met our case definition for CTS at baseline examination and were thus excluded from analysis of incident CTS, and 6 had missing or incomplete data, leaving 711 respondents for incident case analysis. Comparison of baseline characteristics between respondents with follow-up data and those lost to follow-up revealed no differences in baseline characteristics of age, gender, BMI, medical history, or baseline physical exposures. Those lost to follow-up were slightly less likely to meet our case definition of CTS at baseline (12 cases, 3.4%) than those who were followed up (34 cases, 4.5%), though this difference was not statistically significant ($p = .36$). Mean length of follow-up time was 3.3 years (range = 2.2–6.0).

Work Exposures

At baseline, respondents were employed in 81 separate SOC codes. By the retest visit, 320 (45%) respondents had changed jobs at least once; overall, respondents held an average of 1.76 jobs during the observation period. Table 1 shows the 10 most frequent longest jobs held by each respondent. Four of the most common jobs were in the construction trades, accounting for 35.4% of our cohort.

To illustrate the range of values contained in O*NET and the assignment of different values to different work types, Table 2 shows the five jobs with the highest mean values for dynamic strength and static strength, and the five most common jobs that had scores of zero for both dynamic and static strength. Construction and public safety workers had the highest strength demands, whereas many office jobs had scores of zero for both static and dynamic strength requirements. Table 2 also shows the five jobs with the highest and lowest mean for repetitive movements among jobs held by our study population. High-repetition jobs included jobs in service, assembly, office, and construction work, whereas professional positions and sales had the lowest repetition scores.

As shown in Table 3, the cohort was predominantly male and young, with a low prevalence of chronic diseases including diabetes or arthritis reported at any time in the study. At the time of follow-up, 66 respondents had hand symptoms meeting our case definition, whereas 163 met criteria for nerve conduction abnormality, most commonly from an abnormal distal

TABLE 1: Most Frequent Among the Job Held Longest by Each Worker (N = 711)

Job Titles	SOC Code	*n*	%
Construction carpenters	47-2031.01	133	18.7
Maids and housekeeping cleaners	37-2012.00	83	11.7
Floor layers, except carpet	47-2042.00	55	7.7
Drywall and ceiling tile installers	47-2081.00	32	4.5
Sheet metal workers	47-2211.00	32	4.5
Aerospace engineers	17-2011.00	19	2.7
Medical/clinical lab technologists	29-2011.00	16	2.3
Executive secretary and administrative assistants	43-6011.00	13	1.8
Medical records/health information technicians	29-2071.00	12	1.7
Pharmacy technicians	29-2052.00	12	1.7

sensory latency. A total of 31 respondents met our definition of hand symptoms *and* had abnormal nerve conduction study and were thus counted as incident CTS cases; 8 CTS cases were bilateral, 15 were right hand only, and 8 left hand only.

Results of the univariate analyses of CTS epidemiological case status to exposure measures are shown in Table 3, along with distributions of CTS cases and noncases for different personal and work exposure factors. Both age and BMI were associated with incident CTS; diabetes and arthritis were not significant risk factors in this young working population. Three of the six physical exposures studied showed associations with incident CTS. These associations between CTS and the exposures “time spent making repetitive motions” and “static strength” were robust for both the most recent job and for employed time-weighted average. Dynamic strength also showed associations at a p level < .1. The other three studied exposures were not associated with CTS and were not entered into multivariable models, including “time spent using the hand to handle, control, or feel objects,” and the job requirements for “wrist and finger speed” and for “handling and moving objects.”

Results of multivariable analyses are shown in Table 4. Workers’ personal factors of age, BMI, and gender were included in these models. Diabetes and arthritis were excluded from the regression models; due to their low prevalence they were not significant predictors of CTS in our cohort. Repetitive motion, dynamic strength, and static strength were first entered separately as the only exposure variable in a model with the three personal factors. We then entered repetitive motion with each of the two strength variables in separate models. Repetitive motion, dynamic strength, and static strength were all strong and statistically significant predictors of CTS when tested separately in models controlling for age, BMI, and gender. Odds ratios ranging from 3.26 (for exposure on the most recent job) to 2.54 (for employed time-weighted average exposure) were seen for each one-unit increase in the ordinal repetitive movement scale shown in Figure 1. For dynamic strength, odds ratios of 3.57 to 3.59 were seen for risk of CTS in jobs requiring dynamic strength versus those not demanding dynamic strength; for static strength the range was 4.41 to 4.87.

When both repetitive movement and dynamic strength were entered into the same model, the magnitude of the effect for each exposure was reduced, with only repetitive movement remaining statistically significant in the model for exposure on the most recent job. When repetitive motion and static strength were combined, repetitive motion was significant in the model for most recent job, whereas static strength was significant in the employed time-weighted model of exposure. These results are consistent with colinearity between these variables, which was confirmed with statistically significant relationships in five of the six pairwise comparisons. All sensitivity analyses yielded very similar

TABLE 2: Sample of Jobs With Highest and Lowest Exposure Values for Dynamic Strength (0–7 scale) and Repetitive Motion (0–5 scale)

Job Title	SOC Code	*M*
Highest for dynamic strength		
Septic tank servicers and sewer pipe cleaners	47-4071.00	3.13
Carpet installers	47-4071.00	3.12
Correctional officers and jailers	33-3012.00	3.00
Construction carpenters	47-2031.01	3.00
Reinforcing iron and rebar workers	47-2171.00	3.00
Highest for static strength		
Construction carpenters	47-2031.01	4.25
Carpet installers	47-4071.00	4.25
Emergency medical technicians and paramedics	29-2041.00	4.00
Cement masons and concrete finishers	47-2051.00	4.00
Police patrol officers	33-3051.01	3.88
Jobs requiring no dynamic or static strength		
Marketing managers	11-2021.00	0.00
Sales managers	11-2022.00	0.00
Administrative services managers	11-3011.00	0.00
Computer and information systems managers	11-3021.00	0.00
Purchasing managers	11-3061.00	0.00
Highest for repetitive movements		
Hairdressers, hairstylists, and cosmetologists	39-5012.00	4.81
Team assemblers	51-2092.00	4.74
Medical transcriptionists	31-9094.00	4.72
Reinforcing iron and rebar workers	47-2171.00	4.70
Cooks, short order	35-2015.00	4.67
Lowest for repetitive movements		
Real estate sales agents	41-9022.00	1.68
Personal financial advisors	13-2052.00	1.77
Sales representatives, wholesale and manufacturing, technical and scientific products	41-4011.00	1.78
Industrial engineers	17-2112.00	1.79
Occupational health and safety specialist	29-9011.00	1.84

results to primary multivariable mixed logistic regression models (results not shown). We found no statistically significant interactions between the physical exposure variables and the demographic variables of age, BMI, and gender. When models were run separately for men and women (controlling for age and BMI), we found a larger effect size for employed time-weighted repetitive motion among women (OR = 5.12, 95% CI = 1.19–22.07) than among men (OR = 1.74, 95% CI = 0.61–4.99).

DISCUSSION

This study found strong relationships between CTS and workplace physical exposures assessed via a JEM, after adjusting for age, gender, and BMI. Our findings of associations between CTS and workplace exposures to forceful and repetitive motions are consistent with those of studies that assessed physical exposures via observation or direct measurement (Bonfiglioli et al., 2012; Burt et al., 2011; Silverstein et al., 2010). Our study found a higher incidence of CTS in work-

TABLE 3: Distributions of Demographic and Clinical Characteristics (N = 711), With Univariate Analyses of Associations With Incident CTS

	Overall	CTS (n = 31)	No CTS (n = 680)	OR (95% CI)	p
	M (SD)	M (SD)	M (SD)		
Age	30.6 (10.5)	34.3 (12.0)	30.5 (10.4)	1.03 (1.00, 1.06)	**.05**
Body mass index (kg/m^2)	28.2 (6.2)	31.6 (7.5)	28.0 (6.1)	1.08 (1.03, 1.13)	**<.01**
Years of follow-up	3.3 (0.9)	3.0 (0.7)	3.3 (0.9)	0.62 (0.38, 1.01)	.06
Handling and moving objects (0–7 scale)					
Most recent job	4.1 (1.5)	4.2 (1.4)	4.1 (1.5)	1.16 (0.89, 1.51)	.27
Weighted by employed time	4.1 (1.5)	4.2 (1.3)	4.1 (1.5)	1.10 (0.82, 1.46)	.53
Wrist and finger speed (0–7 scale)					
Most recent job	1.3 (1.0)	1.2 (1.0)	1.3 (1.0)	1.21 (0.71, 2.05)	.48
Weighted by employed time	1.3 (0.9)	1.2 (1.0)	1.3 (0.9)	0.96 (0.59, 1.58)	.88
Time spent making repetitive motions (0–5 scale)					
Most recent job	3.6 (0.6)	3.9 (0.5)	3.5 (0.6)	**3.62 (1.45, 9.07)**	**.006**
Weighted by employed time	3.6 (0.5)	3.8 (0.5)	3.6 (0.5)	**2.95 (1.07, 8.15)**	**.04**
Time spent using your hands to handle, control, or feel objects (0–5 scale)					
Most recent job	3.8 (0.9)	4.1 (0.8)	3.8 (0.9)	1.65 (0.97, 2.80)	.06
Weighted by employed time	3.9 (0.9)	4.0 (0.8)	3.8 (0.9)	1.35 (0.85, 2.16)	.31
	n (%)	n (%)	n (%)	OR (95% CI)	p
Female gender	253 (35.6)	13 (41.9)	240 (35.3)	1.32 (0.64, 2.75)	.45
Diabetes mellitus	24 (3.4)	2 (6.5)	22 (3.2)	2.06 (0.46, 9.20)	.34
Arthritis (osteoarthritis or rheumatoid arthritis)	44 (6.2)	2 (6.5)	42 (6.2)	1.05 (0.24, 4.54)	.95
Hand symptoms in one or more fingers	75 (10.6)	31 (100.0)	44 (6.5)	n/a	n/a
Abnormal nerve conduction study	163 (22.9)	31 (100.0)	132 (19.4)	n/a	n/a
Abnormal DML	89 (12.5)	16 (51.6)	73 (10.7)	n/a	n/a
Abnormal DSL	117 (16.5)	25 (80.7)	92 (13.5)	n/a	n/a
Abnormal MUDS	91 (12.8)	22 (71.0)	69 (10.2)	n/a	n/a
Dynamic strength important to job					
Most recent job	531 (74.7)	28 (90.3)	499 (73.4)	2.95 (0.93, 9.38)	.07
Weighted by employed time	527 (74.1)	28 (90.3)	500 (73.5)	2.95 (0.91, 9.55)	.07
Static strength important to job					
Most recent job	472 (66.4)	27 (87.1)	445 (65.4)	**3.24 (1.11, 9.51)**	**.03**
Weighted by employed time	470 (66.1)	27 (87.1)	442 (65.0)	**3.28 (1.09, 9.87)**	**.03**

Note. CTS = carpal tunnel syndrome; DML = distal motor latency; DSL = distal sensory latency; MUDS = sensory median ulnar difference. Bold values indicate significance.

ers whose jobs were rated by O*NET as requiring more time spent making repetitive motions, whose jobs required static strength (defined by O*NET as “the ability to exert maximal muscle force to lift, push, pull, or carry objects”) and whose jobs required dynamic strength (defined as “the ability to exert muscle force repeatedly or continuously over time”).

TABLE 4: Multivariable Mixed Logistic Regression Models of CTS Epidemiologic Case Status Outcome to Exposure Measures Adjusting for Age, BMI, and Gender (N = 711)

	Most Recent Job		Employed-Time Weighted	
	OR (95% CI)	p	OR (95% CI)	p
Repetitive motion	**3.26 (1.37, 7.76)**	**<.01**	2.54 (1.00, 6.44)	.05
Age	1.02 (1.00, 1.05)	.1	1.02 (1.00, 1.05)	.09
Body mass index (kg/m^2)	**1.06 (1.01, 1.12)**	**.03**	**1.07 (1.01, 1.13)**	**.02**
Female gender	0.81 (0.33, 2.01)	.65	0.87 (0.33, 2.26)	.77
Dynamic strength importance (Y/N)	**3.59 (1.04, 12.37)**	**.04**	3.57 (0.98, 13.00)	.05
Age	1.03 (1.00, 1.05)	.05	1.03 (1.00, 1.06)	.05
Body mass index (kg/m^2)	**1.07 (1.02, 1.13)**	**<.01**	**1.07 (1.01, 1.14)**	**.03**
Female gender	1.06 (0.43, 2.61)	.89	1.17 (0.40, 3.37)	.78
Static strength importance (Y/N)	**4.41 (1.40, 13.92)**	**.01**	**4.87 (1.51, 15.72)**	**<.01**
Age	1.03 (1.00, 1.05)	.05	**1.03 (1.00, 1.05)**	**.03**
Body mass index (kg/m^2)	**1.07 (1.01, 1.13)**	**.02**	**1.07 (1.01, 1.13)**	**.03**
Female gender	1.35 (0.57, 3.18)	.49	1.47 (0.61, 3.55)	.39
Repetitive motion	**2.75 (1.16, 6.55)**	**.02**	1.98 (0.77, 5.09)	.16
Dynamic strength importance (Y/N)	2.14 (0.56, 8.22)	.27	2.67 (0.68, 10.43)	.16
Age	1.03 (0.99, 1.06)	.13	1.03 (0.99, 1.06)	.14
Body mass index (kg/m^2)	1.07 (1.01, 1.12)	.02	1.07 (1.01, 1.13)	.01
Female gender	0.93 (0.40, 2.17)	.87	1.00 (0.43, 2.33)	1
Repetitive motion	**2.48 (1.05, 5.86)**	**.04**	1.63 (0.69, 3.85)	.27
Static strength importance (Y/N)	2.70 (0.85, 8.55)	.09	**3.48 (1.05, 11.54)**	**.04**
Age	1.03 (1.00, 1.05)	.07	1.02 (1.00, 1.05)	.06
Body mass index (kg/m^2)	**1.07 (1.01, 1.12)**	**.02**	**1.07 (1.01, 1.13)**	**.03**
Female gender	1.09 (0.49, 2.43)	.84	1.24 (0.54, 2.89)	.61

Note. Bold values indicate significance.

Occupational epidemiological studies have frequently relied on the use of a JEM to assign exposure status to large numbers of workers in a particular plant or industry (Plato & Steineck, 1993). The attraction of the method is that a JEM provides an inexpensive method to convert coded occupational titles into exposure estimates for epidemiological studies. Because no distinction is made between diseased and nondiseased respondents and a person-by-person approach to exposure assignment is not used, the potential for differential information bias is markedly decreased (Kauppinen, Toikkanen, & Pukkala, 1998). Although this technique has frequently been used in studies of occupational cancers, fewer studies have used a job-exposure matrix to assign physical exposures such as posture, repetition, or force. JEMs have probably been underutilized in musculoskeletal disease epidemiology for several reasons.

Many work-related musculoskeletal disorders are assumed to have relatively short latency periods, making recent work exposures the most relevant for study. This reduces one theoretical advantage of JEMs, their ability to account for past exposures. Many of the studies that have used a JEM to estimate physical exposures have studied osteoarthritis, where cumulative exposure over decades is assumed to be important in disease etiology (D'Souza, Keyserling, Werner, Gillespie, & Franzblau, 2007; D'Souza et al., 2008; Felson et al., 1991; Seidler et al., 2001; Vingård, Alfredsson, Goldie, & Hogstedt, 1991; Vingård, Hogstedt, et al., 1991). These studies used job titles to group workers in exposure groups, and most assigned exposures to these job titles through expert opinion within the study or by reference to external sources of expert opinion such as O*NET or the U.S. Dictionary of Occupational Titles (the predecessor to O*NET). The study by Seidler et al. (2001) used self-reported exposure to lifting as the basis for their job exposure groupings, but rather than using individually reported data as the exposure for each individual, they grouped respondents by the mean of physical exposures reported by the nondiseased respondents in each job title group. This is a potentially attractive approach that makes use of workers' knowledge of job exposures but reduces the potential for some types of information bias.

A few studies of upper-extremity disorders including CTS have used a JEM. Blanc, Faucett, Kennedy, Cisternas, and Yelin (1996) used a job and industry matrix to assign workplace repetitive hand and wrist bending to a cohort of more than 33,000 persons in a study of work disability from CTS. They found that repetitive hand or wrist bending in the occupation and industry of last employment was a significant factor predictive of CTS-attributed work disability, even after taking into account sociodemographic factors and health status. By assigning the mean value of hand or wrist bending to all workers in the same cell, this cross-sectional, questionnaire-based study filled in missing data and reduced the likelihood of information bias resulting from symptomatic workers reporting higher exposures than nonsymptomatic workers with the same job duties. A subsequent study (Carmona, Faucett, Blanc, & Yelin, 1998) using values from this same JEM showed that repetitive hand and wrist bending was a significant factor predicting rate of return to work following CTS surgery. In a series of papers, Svendsen, Johnsen, Fuglsang-Frederiksen, and Frost (2012) used a JEM to study work-related biomechanical factors in ulnar neuropathy, by first coding jobs using a Danish national job classification schema, grouping them into exposure related groups, and then using consensus of experts to rate job groupings by duration or intensity of exposure to several variables. Boyer and colleagues (2009) created a JEM among hospital workers, using both job observations and O*NET data to create job specific estimates of manual handling, force requirements, and bending and twisting of the body, which were used to predict injuries claimed under workers' compensation.

To our knowledge, only one previous study has used O*NET to evaluate the risk of CTS related to workplace physical exposures. In this study (Armstrong, Dale, Franzblau, & Evanoff, 2008), our research group examined the risk of prevalent CTS at the baseline examination of the 1,107 newly hired workers in the PrediCTS study by estimating exposures during the most recent job held prior to the new job. We assessed both self-reported job exposures and job-title-based exposures, using a different procedure for analyzing O*NET data than that used in the present study. In this earlier study, we extracted a set of 11 O*NET variables and used a factor analysis to collapse these data into a smaller number of variables. Using factor analysis, physical exposure variables from the O*NET database were collapsed into three factors, characterized as upper-extremity force requirement, manual dexterity, and repetition based on the O*NET items with the highest loadings on each factor. The force and repetition requirements of the previous job, but not the manual dexterity requirement, were significant predictors of CTS in models adjusting for demographic factors. In the present study we opted to analyze a smaller number of exposure variables and not to combine them as factors, primarily to increase the generalizability of our results. As described by Cifuentes et al. (2010), the results of exposure metrics created via factor analysis may be highly dependent on which jobs are included in the study and how many respondents are in each job; different work organizational factors may cause different exposures to coincide, further limiting generalizability from one work setting to another. We felt that use of discrete items from O*NET would make our findings more directly applicable to multiple work settings.

This paper demonstrates that a JEM using publicly available data on work physical demands can find meaningful associations with the incidence of CTS. It is likely that this same approach would be feasible with other upper-extremity musculoskeletal disorders. There are a number of limitations to the use of JEMs—in particular the lack of information about within-job variability, questions about the validity of the exposure data, the need to accurately and reliably classify jobs using the SOC, and other issues of exposure misclassification. There has been one study to date examining the convergent validity of O*NET exposures to the upper extremity via comparison to other methods. This study was performed in a subset of the workers in the PrediCTS study (Gardner et al., 2010) and compared O*NET ratings to self-reported and observed data in the same workers expressed as intraclass correlation coefficients (ICCs). The study found good agreement between the O*NET rating of static strength and the observed duration of forceful grip (ICC = .53), fair agreement between the O*NET rating of dynamic strength and observed forceful grip (ICC = .36), but poor agreement between the O*NET rating of repetitive motions and the observed hand activity level. It is not yet known what differences in exposure response relationships may result when different methods of exposure assessment (i.e., directly measured, observed, self-reported, or job title derived) are applied in the same worker populations. This is an interesting question for future studies.

Assignment of biomechanical exposures based on job titles may result in significant exposure misclassification for a variety of reasons. Exposure items linked to job titles may lack the specificity required for occupational health research, and the item definitions used by O*NET or other data sources may not match the exposures most relevant to causation. Another drawback is that all workers in the same job are assigned the same exposures, thus reducing variability in exposures between workers that could be revealed by individual-level exposure measures. Finally, the O*NET data and SOC codes are specific to workers in the United States, and application of either should be used cautiously in populations from other countries. Despite these drawbacks, JEMs can be useful for large population studies where more precise exposure data are not available. In particular, O*NET can provide estimates of average work exposures for studies where job titles are available but other desired information about working conditions was not collected or is not logistically feasible to collect. As a publicly available and free data set, O*NET provides an attractive option for adding data to epidemiology studies that would otherwise not have occupational exposure data.

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KEY POINTS

- The incidence of carpal tunnel syndrome was associated with repetitive motions and job strength requirements described in a publically available database of job requirements.
- Job exposure matrices based on job titles can be useful as an exposure measure when more precise information is not available

REFERENCES

Armstrong, T., Dale, A. M., Franzblau, A., & Evanoff, B. A. (2008). Risk factors for carpal tunnel syndrome and median neuropathy in a working population. *Journal of Occupational and Environmental Medicine*, *50*, 1355–1364.

Barcenilla, A., March, L. M., Chen, J. S., & Sambrook, P. N. (2012). Carpal tunnel syndrome and its relationship to occupation: A meta-analysis. *Rheumatology*, *51*, 250–261.

Bernard, B. (1997). *Musculoskeletal disorders and workplace factors: A critical review of epidemiologic evidence for work-related musculoskeletal disorders of the neck, upper extremity, and low back*. (NIOSH Pub. No. 97-141). Washington, DC: U.S. Department of Health and Human Services.

Blanc, P. D., Faucett, J., Kennedy, J. J., Cisternas, M., & Yelin, E. (1996). Self-reported carpal tunnel syndrome: Predictors of work disability from the National Health Interview Survey Occupational Health Supplement. *American Journal of Industrial Medicine*, *30*, 362–368.

Bonfiglioli, R., Mattioli, S., Armstrong, T., Graziosi, F., Marinelli, F., Farioli, A., & Violante, F. (2012). Validation of the ACGIH TLV for hand activity level in the OCTOPUS cohort: A two-year longitudinal study of carpal tunnel syndrome. *Scandinavian Journal of Work, Environment & Health*. Advance online publication. doi:10.5271/sjweh.3312

Boyer, J., Galizzi, M., Cifuentes, M., d'Errico, A., Gore, R., Punnett, L., & Slatin, C. (2009). Ergonomic and socioeconomic risk factors for hospital workers' compensation injury claims. *American Journal of Industrial Medicine*, *52*, 551–562.

Burt, S., Crombie, K., Jin, Y., Wurzelbacher, S., Ramsey, J., & Deddens, J. (2011). Workplace and individual risk factors for carpal tunnel syndrome. *Journal of Occupational and Environmental Medicine*, *68*, 928–933.

Carmona, L., Faucett, J., Blanc, P. D., & Yelin, E. (1998). Predictors of rate of return to work after surgery for carpal tunnel syndrome. *Arthritis Care and Research*, *11*, 298–305.

Cifuentes, M., Boyer, J., Lombardi, D. A., & Punnett, L. (2010). Use of O*NET as a job exposure matrix: A literature review. *American Journal of Industrial Medicine*, *53*, 898–914.

Dale, A. M., Strickland, J., Symanzik, J., Franzblau, A., & Evanoff, B. A. (2008). Reliability of hand diagrams for the epidemiologic case definition of carpal tunnel syndrome. *Journal of Occupational Rehabilitation*, *18*, 223–248.

D'Souza, J. C., Keyserling, W. M., Werner, R. A., Gillespie, B., & Franzblau, A. (2007). Expert consensus ratings of job categories from the Third National Health and Nutrition Examination Survey (NHANES III). *American Journal of Industrial Medicine*, *50*, 608–616.

D'Souza, J. C., Werner, R. A., Keyserling, W. M., Gillespie, B., Rabourn, R., Ulin, S., & Franzblau, A. (2008). Analysis of the Third National Health and Nutrition Examination Survey (NHANES III) using expert ratings of job categories. *American Journal of Industrial Medicine*, *51*, 37–46.

Felson, D. T., Hannan, M. T., Naimark, A., Berkeley, J., Gordon, G., Wilson, P. W., & Anderson, J. (1991). Occupational physical demands, knee bending, and knee osteoarthritis: Results from the Framingham Study. *Journal of Rheumatology*, *18*, 1587–1592.

Franzblau, A., Werner, R. A., Albers, J. W., Grant, C. L., Olinski, D., & Johnston, E. (1994). Workplace surveillance for carpal tunnel syndrome using hand diagrams. *Journal of Occupational Rehabilitation*, *4*,185–198.

Gardner, L. I., Landsittel, D. P., Nelson, N. A., & Pan, C. S. (2000). Misclassification of physical work exposures as a design issue for musculoskeletal intervention studies. *Scandinavian Journal of Work, Environment & Health*, *26*, 406–413.

Gardner, B. T., Lombardi, D. A., Dale, A. M., Franzblau, A., & Evanoff, B. A. (2010). Reliability of job-title based physical work exposures for the upper extremity: Comparison to self-reported and observed exposure estimates. *Journal of Occupational and Environmental Medicine*, *67*, 538–547.

Hansson, G. A., Balogh, I., Bystrom, J. U., Ohlsson, K., Nordander, C., Asterland, P., . . . Skerfving, S. (2001). Questionnaire versus direct technical measurements in assessing postures and movements of the head, upper back, arms and hands. *Scandinavian Journal of Work, Environment & Health*, *27*, 30–40.

Kauppinen, T., Toikkanen, J., & Pukkala, E. (1998). From cross-tabulations to multipurpose exposure information systems: A new job-exposure matrix. *American Journal of Industrial Medicine*, *33*, 409–417.

Mathiassen, S. E., & Paquet, V. (2010). The ability of limited exposure sampling to detect effects of interventions that reduce the occurrence of pronounced trunk inclination. *Applied Ergonomics*, *41*, 295–304.

Morel, J. G., Bokossa, M. C., & Neerchal, N. K. (2003). Small sample correction for the variance of GEE estimators. *Biometrical Journal*, *45*, 395–409.

Occupational Information Network, U.S. Department of Labor/Employment and Training Administration. (2012a). *O*NET data collection program website*. Retrieved from https://onet.rti.org/

Occupational Information Network, U.S. Department of Labor/Employment and Training Administration. (2012b). *O*NET OnLine website*. Retrieved from http://www.onetonline.org/

Occupational Information Network, U.S. Department of Labor/Employment and Training Administration. (2012c). *Production database—O*NET 16.0*. Retrieved from: http://www.O*NETcenter.org/database.html

Plato, N., & Steineck, G. (1993). Methodology and utility of a job-exposure matrix. *American Journal of Industrial Medicine*, *23*, 491–502.

Seidler, A., Bolm-Audorff, U., Heiskel, H., Henkel, N., Roth-Kuver, B., Kaiser, U., . . . Elsner, G. (2001). The role of cumulative physical work load in lumbar spine disease: Risk factors for lumbar osteochondrosis and spondylosis associated with chronic complaints. *Occupational & Environmental Medicine*, *58*, 735–746.

Silverstein, B. A., Fan, Z. J., Bonauto, D. K., Bao, S., Smith, C. K., Howard, N., & Viikari-Juntura, E. (2010). The natural course of carpal tunnel syndrome in a working population. *Scandinavian Journal of Work, Environment & Health*, *36*, 384–393.

Svendsen, S. W., Johnsen, B., Fuglsang-Frederiksen, A., & Frost, P. (2012). Ulnar neuropathy and ulnar neuropathy-like symptoms in relation to biomechanical exposures assessed by a job exposure matrix: A triple case–referent study. *Occupational & Environmental Medicine*, *69*, 773–780. doi:10.1136/oemed-2011-100499

Viikari-Juntura, E., Rauas, S., Martikainen, R., Kuosma, E., Riihimaki, H., Takala, E. P., & Saarenmaa, K. (1996). Validity of self-reported physical work load in epidemiologic studies on musculoskeletal disorders. *Scandinavian Journal of Work, Environment & Health*, *22*, 251–259.

Vingård, E., Alfredsson, L., Goldie, I., & Hogstedt, C. (1991). Occupation and osteoarthrosis of the hip and knee. *International Journal of Epidemiology*, *20*, 1025–1031.

Vingård, E., Hogstedt, C., Alfredsson, L., Fellenius, E., Goldie, I., & Köster, M. (1991). Coxarthrosis and physical work load. *Scandinavian Journal of Work, Environment & Health*, *17*, 104–109.

Werner, R. A., Franzblau, A., Gell, N., Hartigan, A. G., Ebersole, M., & Armstrong, T. J. (2005). Incidence of carpal tunnel syndrome among automobile assembly workers and assessment of risk factors. *Journal of Occupational and Environmental Medicine*, *47*, 1044–1050.

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