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Using Observation and Self-report to Predict Mean, 90th Percentile, and Cumulative Low Back Muscle Activity in Heavy Industry Workers

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Occupational injury research depends on the ability to accurately assess workplace exposures for large numbers of workers. This study used mixed modeling to identify observed and self-reported predictors of mean, 90th percentile, and cumulative low back muscle activity to help researchers efficiently assess physical exposures in epidemiological studies. Full-shift low back electromyography (EMG) was measured for 133 worker-days in heavy industry. Additionally, full-shift, 1-min interval work-sampling observations and post-shift interviews assessed exposure to work tasks, trunk postures, and manual materials handling. Data were also collected on demographic and job variables. Regression models using observed variables predicted 31–47% of the variability in the EMG activity measures, while self-reported variables predicted 21–36%. Observation-based models performed better than self-report-based models and may provide an alternative to direct measurement of back injury risk factors.

Keywords: determinants of exposure; ergonomics; exposure assessment; exposure prediction; low back disorders; observation; self-report

INTRODUCTION

Back disorders are a prevalent and expensive problem in working life (Shelerud, 2006; Rubin, 2007). In order to address the issue of back disorders, researchers need accurate information on working exposures. High-resolution direct measurement is often considered a preferred method for occupational exposure assessment (Burdorf, 1992; Winkel and Mathiassen, 1994; Wells *et al.*, 1997; van der Beek and Frings-Dresen, 1998; Burdorf and van der Beek, 1999; David, 2005). Although not a perfect measure of spinal compression and risk for back injury, electromyography (EMG) is a direct measurement method that can be used to assess exposures of the low back in contexts where traditional biomechanical methods, such as video analysis or motion capture systems, are not feasible. EMG has been used successfully in workplace settings to estimate muscle loads (Keir and MacDonell, 2004; Jones and Kumar, 2007) and spinal compression (Village *et al.*, 2005).

Direct measurement tends to be costly and time-intensive, and while it has been used for large numbers of workers in the field (Hansson *et al.*, 2001; Balogh *et al.*, 2004), it is more common to use such

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techniques for short durations, small numbers of workers, (Cooper and Ghassemieh, 2007; Jones and Kumar, 2007) or in simulated work tasks (Moore and Garg, 1995; Keir and MacDonell, 2004; Lavender *et al.*, 2007). Herein lies a trade-off; large-scale epidemiological studies require accurate methods that can also be efficiently applied over large samples. Observation and worker self-reporting have been used as less expensive ergonomic assessment tools for large numbers of workers, although these methods (and their costs) can vary substantially from postal surveys (Sobti *et al.*, 1997) to intensive multiday observational sampling (Village *et al.*, 2009).

'Determinants of exposure' modeling offers a method for assessing the relationship between direct measurements and less costly observation or self-report measurements of physical exposures. This involves predicting a measured exposure (in this study, direct measures of muscle activity by EMG) using characteristics that directly or indirectly increase or decrease that exposure (as measured by observation or self-reports of physical exposures). This methodology has long been used in industrial hygiene to estimate a wide variety of airborne and chemical exposures (Nieuwenhuijsen *et al.*, 1995; Preller *et al.*, 1995; Burstyn *et al.*, 1997; Burstyn and Teschke, 1999; You *et al.*, 2007). Exposure modeling has also been attempted for physical exposures, including modeling whole-body vibration using observed and self-reported driver, route, and vehicle characteristics (Chen *et al.*, 2004), arm inclination based on task diaries (Svendsen *et al.*, 2005), and trapezius EMG based on observed tasks or occupations (Mathiassen *et al.*, 2005). More recently, this methodology has been applied to model inclinometer-assessed trunk posture using observed and self-reported work exposures (Teschke *et al.*, 2009).

The goal of this study was to develop exposure prediction models for mean, 90th percentile, and cumulative low back EMG activity using exposure self-reports and observations. Two sets of models were developed, one to identify observed predictors of exposure and another to identify self-reported predictors. The larger goal is to help researchers efficiently and effectively measure physical exposures for studies of work-related injury.

MATERIALS AND METHODS

Worker sample

This study measured full-shift EMG of the lumbar muscles of workers from 50 different worksites in British Columbia within the heavy industrial sectors of construction, forestry, transportation, warehousing, and wood and paper products from September 2004 to January 2006. Human subject procedures were approved by the University of British Columbia's Behavioural Research Ethics Board. Workers were selected at random from those with accepted workers' compensation back strain claims for the year 2001 to identify jobs that would have exposure to physical risk factors. Eligible workers were currently working in the five target industries and did 'shop floor' rather than administrative jobs. After subjects agreed to participate, researchers contacted their employers to obtain permission to conduct worksite measurements and to recruit an additional one to four coworkers. Set-up, measurements, and interviews were conducted during regular work time. Concurrent measurements were made over a full work shift using EMG, observations, and worker interviews.

Full-shift EMG measurements were successfully completed on 92 individual workers and 45% were % measured on 2 days for a total of 133 worker-days. The lag between repeat measurement days on the same worker ranged from 1 to 439 days (mean = 93, SD = 64). Observation and self-report data were available for all worker-days. Demographic data and job titles of the worker sample are summarized by industry in Table 1.

EMG measurement

Full-shift EMG measurements were made using a portable data collection system with on-board memory (ME3000P4/ME3000P8; Mega Electronics, Kuopio, Finland) and disposable Ag–AgCl electrodes (Blue Sensor N-00-S; Ambu, Ballerup, Denmark). Electrodes were placed bilaterally over the erector spinae at approximately the level of L4/L5, with a 20-mm interelectrode spacing and a ground electrode and preamplifier placed on the posterior aspect of the iliac crest. Although additional electrodes have been used in laboratory-based investigations to account for coactivation and flexion-relaxation phenomenon (Ferguson *et al.*, 2002), this was impractical for industrial settings (Village *et al.*, 2005). Signals were collected at 1000 Hz and filtered internally using an 8- to 500-Hz band pass filter. Root-mean-square values were data-logged at 10 Hz. During work breaks, data from the portable system were downloaded to a laptop computer. EMG data were collected for the full shift excluding breaks (mean 6.2 h, range of 5.5–10.3 h).

A submaximal reference contraction effort was employed to calibrate EMG data collected during the shift. The reference effort involved a static 45° forward trunk flexion while holding an 11.5-kg

Table 1. Demographic characteristics and typical job titles for study participants in heavy industry

Exposure metric	Construction	Forestry	Transportation	Warehousing	Wood products	All industries combined
N (workers)	18	19	22	14	19	92
% Male	100	100	97.2	92.3	89.1	95.3
Mean Height in cm (SD)	179 (6.1)	176 (7.3)	177.6 (8.9)	180.3 (8.9)	177.0 (7.3)	178.1 (7.9)
Mean Weight in kg (SD)	80.9 (11.4)	89.9 (19.2)	83.6 (15.9)	85.7 (15.7)	84.9 (16.2)	85.2 (16.1)
Mean Age, in years, on sampling day (SD)	43 7 (9.8)	48.5 (9.8)	38.9 (9.6)	38.8 (11.3)	43.0 (13.2)	42.2 (12)
Mean shift length (SD)	8.39 (0.78)	7.97 (1.5)	9.6 (1.8)	8.3 (1.1)	8.3 (1.2)	8.5 (1.4)
Typical job titles	Construction carpenter, construction laborer, construction supervisor, other construction trades	Boomman, faller, heavy equipment operator, heavy-duty equipment mechanic, logging machinery operators	Cabinet maker, forklift operator, lumber grader, puller, papermaking/coating operator	Air transport ramp attendants, automotive mechanic, bus driver, ferry worker, storekeepers and parts clerks, truck driver, warehouse person	Forklift operator, other warehousing	—

weight. Trunk flexion was measured using a 12-inch (30 cm) hand-held goniometer (Baseline Instruments Inc.) with bubble level for vertical alignment. The reference effort was performed twice for 5 s at the beginning of the shift. In order to normalize measurement data across workers, all EMG data collected during the shift were expressed as a percentage of this reference voluntary effort (%RVE).

A detailed description of EMG data collection challenges (including cable snags and loss of electrode adhesion) have been reported elsewhere (Trask *et al.*, 2007). When interruptions were encountered, the researchers applied new electrodes and recalibrated. This was not always feasible and EMG measures were only included in this analysis if data were available for at least half of the work shift. To identify motion artifacts, the data were visually inspected and artifacts were excluded from analysis. After data cleaning, the resulting sample used for this analysis was 133 measurement days (75% of 178 attempted).

Three 'exposure metrics' were calculated for each individual's work shift data: mean represented central tendency, 90th percentile represented peak exposure levels, and cumulative exposure measured the sum of daily exposures. The 90th percentile (measured in %RVE) has been used as a measure of 'peak' load in previous studies (Mathiassen *et al.*, 2002; Moller *et al.*, 2004; Nordander *et al.*, 2004). Cumulative EMG activity was expressed in %RVE-minutes exposure and was calculated over the whole shift regardless of shift length. All three EMG metrics are presented as they may each represent different aspects of back injury risk. In an epidemiological study of auto workers, cumulative exposure predicted back injury risk independently of peak loading (Norman *et al.*, 1998), and both types of loading have been shown to damage tissues during *in vitro* studies (Brinkmann *et al.*, 1988; Drake and Callaghan, 2009).

Investigation of EMG calibration

Additional calibration tests were conducted at the beginning and end of the shift to identify any drift, fatigue, or other differences occurring over the course of a full shift. In addition to the 45° flexion reference contraction with the 11.5-kg weight, muscle activity was also recorded for standing upright, for 45° flexion without a weight, and for 60° of flexion with an 11.5-kg weight to represent some typical positions and weights seen in industrial tasks. Two samples of each maneuver were collected both before and after the shift. Altogether, 16 calibrations were planned per subject per day: two sessions × four positions × two repeats per position. These data collection resulted in 916 pairs of pre-post calibration measurements. Pairs of measurements were matched for subject, measurement session, posture and weight, etc. Rather than using null hypothesis statistical testing, equivalence testing was used to compare the pre- and post-shift calibration measurements (Ngatia *et al.*, 2009). The scientifically important limit '*L*' was set to 5 μV, since differences within ±5 μV were thought unlikely to influence the results in a substantial way. In addition, linear regression models were used to identify any relationships between muscle activity (in microvolt) and pre- versus post-shift, controlling for left versus right side, Trial 1 versus Trial 2, and reference positions 1 through 4. Multiple linear regression mixed models were developed using 'individual' and 'electrode session' as random effects. An 'electrode session' represents the unique electrode/skin interface for each shift measurement of an individual. Task condition, pre/post-shift, right/left side, and trial number were fixed effects.

Observation data collection

Observations of physical exposures were made by trained observers throughout the work shift (excluding breaks) starting after EMG instrumentation and calibration and ending with deinstrumentation at the shift's completion. Observations were recorded by trained research personnel once every minute using the BackEST (Back Exposure Sampling Tool) observation tool (Village *et al.*, 2009). In brief, these variables were general task or activity, item or power tool in hands, items worn (such as a tool belt), general body posture (such as standing, walking, and kneeling), trunk posture (twisting, lateral flexion, and categories of trunk flexion), presence of trunk support, and manual materials handling (type of load, horizontal distance, weight, and force estimate). The total observed time a worker was exposed to a given risk factor was used as a predictive variable for the cumulative EMG models, whereas proportions of observed time exposed to risk factors were used for mean and 90th percentile EMG models. For example, the sum of 1-min observations spent standing was divided by the total number of 1-min observations to yield a percentage of time spent standing. Pilot testing methods, validity and reliability data, and a sample of the BackEST observational tool are reported in Village *et al.* (2009).

Self-report data collection

A post-shift interview was conducted with each worker to assess self-reported exposures during that shift. The questionnaire instrument was pilot tested on industrial workers prior to data collection and results based on this instrument have been published elsewhere (Teschke et al., 2009). Using diagrams of activities and postures as visual cues, workers were asked to identify the presence or absence of general activities such as standing, walking, kneeling, trunk postures (including twisting, lateral flexion, and categories of trunk flexion), and manual materials handling activities (including type of load, horizontal distance, weight, and force estimate). For each exposure, workers were asked to estimate the duration during the work day by selecting a time category: (<5 min, 5–15 min, 15–30 min, 30–45 min, 45–60 min, 1–2 h, 2–4 h, 4–6 h, 6–8 h, and >8 h). The questionnaire aimed to expand on previous questionnaires where exposure categories were binary (Karlqvist *et al.*, 1996) or qualitative (Unge *et al.*, 2005). Hours and minutes were selected because workers tended to report the time in hours and minutes during pilot testing rather than as a percentage or fraction of the shift as in other questionnaires (Stock, 2005).

These times were converted to a percentage of work time by taking the category midpoint and dividing by the shift length. Job title, age, height, weight, hours worked per shift, shifts worked per week, and the number of consecutive shifts worked were also determined during the interview. A copy of the interview instrument can be obtained from the study website at: www.cher.ubc.ca/backstudy.htm.

Statistical analysis: developing the models

Any differences in EMG metrics between industries were assessed using one-way analysis of variance and Tukey's *post hoc* test. EMG exposure prediction models were developed for each of the three metrics: mean, 90th percentile, and cumulative EMG. Separate models were constructed for observed variables and for self-reported variables as predictors of the EMG metrics. Initially, simple linear regression was used to identify relationships between EMG exposure metrics and each of the observed or self-reported exposure variables. Observation variables were offered to subsequent multivariable models if $P < 0.\ 0.1$, while self-reported variables were offered if $P < 0.05$ (more restrictive because there were many more individual self-reported variables available). A correlation matrix of significant independent variables was developed; if independent variables were correlated at Pearson $r \geq 0.70$, then the variable with the lowest bivariate P-value was selected for input to the multivariable model. Supplementary tables 1 and 2 (available at *Annals of Occupational Hygiene* online) show the pairs of variables with correlations higher than 0.70 as well as which ones were eliminated from the models due to these high correlations. All statistical analyses were performed in SAS version 9.1 (SAS Institute Inc., Cary, NC, USA).

When building the final multivariable models, variables significant in bivariate modeling were offered to the multivariable models in 'conceptual groups', in order of their expected relationship to muscle activity, from most to least direct. For example, a model was progressively built offering all postural variables, then all manual materials handling variables, all demographic variables, and finally industry. A list of observed and self-reported variables within their respective conceptual groups can be seen in Tables 3 and 4. Variables that were significant within a conceptual group model were forced into the subsequent multivariable models. We chose to retain variables that were significant when originally offered to the model within their conceptual groups (even when they were not in the final model) to allow variables considered most directly related to exposure to remain in the model. This is similar to a two-stage exposure assessment design (Armstrong, 1995; Duan and Mage, 1997).

Finally, mixed modeling methods were used to account for repeated measurements on the same individuals (Burstyn and Teschke, 1999; Burdorf, 2005). For this study, 'subject' and 'company' were initially offered as random effects to account for any between-subject variability and between-company variability (respectively) not accounted for in the fixed effects; only 'subject' had a significant relationship with exposure and was retained in the models. The proportion of variance determined by 'subject' was calculated for each model. Mixed effects modeling was conducted using backwards stepwise multiple linear regression in SAS.

The proportion of variance explained by each model was estimated by comparing the predicted exposure levels to the actual measured exposure levels. The R^2 between estimated and observed EMG exposures was used as an estimate of the proportion of variance explained by the mixed model.

RESULTS

Investigation of EMG calibration

Pre-shift measures were, on average, 3.2 μV higher than post-shift measures for the same person, position, trial number, and side of the body. The lower limit and upper limit of the equivalence test were 2.4 and 4.1 μV, respectively, within the predetermined limits of ±5 μV. The multivariate model of EMG calibration maneuvers (controlling for subject and measurement session as random effects) confirmed this:

$$\begin{aligned}\text{EMG in } \mu\text{V} = 34.9 &+ 3.06\ (\text{preshift}) \\ &+ 1.0(\text{Trial 1}) + 1.5(\text{left side}) \\ &- 30.4(\text{standing upright}) \\ &- 7.5(\text{standing at } 45\ ^\circ) \\ &+ 1.7(\text{standing at } 45\ ^\circ \text{ with weight}).\end{aligned}$$

Position accounted for the largest proportion of explained EMG variance at 23%, compared to <0.4% for pre- versus post-shift.

EMG exposure metrics by industry

Mean, 90th percentile, and cumulative EMG exposures are presented in Table 2. Overall, the ordinal exposure ranking of the industries was fairly

Table 2. EMG exposure metrics for five heavy industries. All metrics are based on data collected over a full work shift and summarized as mean of means within worker

Exposure metric	Construction (n = 26 worker-days)	Forestry (n = 29 worker-days)	Transportation (n = 30 worker-days)	Warehousing (n = 22 worker-days)	Wood products (n = 26 worker-days)	All industries combined (n = 133 worker-days)
Mean %RVE (SD)	51.7 (13.6)	43.1 (26.4)	29 (12.4)	37.7 (20.2)	37.2 (20.4)	39.6 (20.1)
Fifth percentile RVE (SD)	6.83 (4.91)	1.63 (3.13)	1.98 (4.17)	4.35 (6.98)	3.28 (5.61)	3.45 (5.26)
10th percentile RVE (SD)	9.64 (5.80)	5.79 (6.37)	3.48 (5.79)	6.50 (6.86)	6.85 (6.16)	6.30 (6.42)
50th percentile RVE (SD)	37.4 (14.1)	26.7 (20.7)	16.8 (7.53)	27.8 (17.2)	28.6 (21.2)	26.9 (17.8)
90th percentile RVE (SD)	107.1 (26.0)	84.4 (41.1)	67.5 (27.6)	84.9 (45.0)	80.0 (45.0)	83.8 (36.6)
95th percentile RVE (SD)	127 (33.4)	115 (47.8)	91.1 (38.4)	111 (58.4)	102 (54.2)	109 (47.8)
Cumulative (%RVE·min)	1043 (350)	1264 (625)	967 (716)	931 (604)	1114 (548)	1069 (589)

Table 3. Observed physical exposure variables associated with mean, 90th percentile, and cumulative EMG exposure in final multiple linear regression models, with subject as a random effect

Variable	Mean %RVE		90th percentile %RVE		Cumulative %RVE·min[a]	
Observation	β (slope)	P	β (slope)	P	β (slope)	P
Intercept (average for all subjects)	19.8	<0.0001[b]	43.8	<0.0001[b]	595895	<0.0001[b]
Standing (% time)	0.115	<0.001[b]	0.166	0.316		
Sitting (% time)					−3118	0.041[b]
Trunk position 10–20° (% time)					7295	0.0004[b]
Trunk position 20–45° (% time)	0.236	0.103	0.970	0.010		
Trunk position 45–60° (% time)					17182	0.0004[b]
Trunk position >60° (% time)	0.612	0.0018[b]	1.25	0.0014		
Handling load at extended horizontal distance (% time)	0.134	0.633	0.659	0.229		
4.5- to 10-kg load in hands (% time)	0.910	<0.001[b]	0.987	0.009	22581	<0.0001[b]
10- to 20-kg load in hands (% time)	0.325	0.0641			7535	0.114
'Light' Push/pull force (% time)	0.236	0.144				
Handling loads with two hands			0.298	0.289		
Estimated proportion of variance explained by model	47.2%		42.9%		30.7%	

[a]Independent variables for cumulative EMG activity are in total time.
[b]Variables significant at $P < 0.05$.

Table 4. Self-reported physical exposure variables associated with mean, 90th percentile, and cumulative EMG exposure in final multiple linear regression models, with subject as a random effect

Variable	Mean %RVE		90th percentile %RVE		Cumulative %RVE·min[a]	
Self-report	β (slope)	P	β (slope)	P	β (slope)	P
Intercept (average of subjects)	33.4	<0.0001[b]	78.7	<0.0001[b]	627029	<0.0001[b]
Sitting (% time)	−0.181	0.0023[b]	−0.376	0.0009		
Walking with trunk twisted (% time)					22566	0.0012[b]
Crouching, kneeling, or squatting (% time)	0.202	0.0543				
Sitting and twisting (% time)	−0.226	0.0664	−0.498	0.0403	−7157	0.0268[b]
Construction industry	14.8	0.0054[b]	24.3	0.0131[b]		
Forestry industry	13.3	0.0109[b]	20.0	0.0323[b]		
Wood product industry	4.44	0.369	4.15	0.650		
Warehousing industry	8.75	0.102	13.8	0.158		
Transportation industry	0	Reference	0	Reference		
Manual materials handling (% time)					1332	0.159
4.5- to 10-kg load in hands (% time)			0.165	0.337		
Handling load at extended horizontal distance (% time)			0.710	0.0040[b]	5214	0.124
Estimated proportion of variance explained by model	36.0%		36.0%		21.0%	

[a]Independent variables for cumulative EMG activity are in total time.
[b]Variables significant at $P < 0.05$.

consistent across the metrics. The construction industry had significantly higher measures of mean and 90th percentile EMG activity compared to the transportation industry, while the forestry industry had significantly higher measures than the transportation industry for all three exposure metrics.

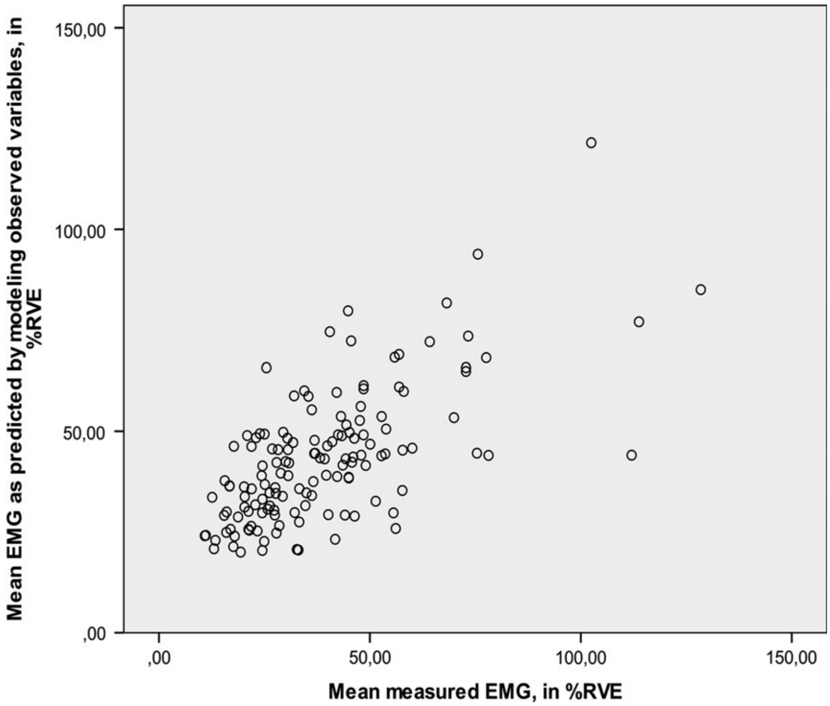

Fig. 1. Scatter plot of predicted mean EMG as modeled by observed variables (*y*-axis) by mean measured EMG (*x*-axis), all in %RVE. Regression equation: Observed EMG = 0.538 (Measured EMG) + 22.4. $R^2 = 0.67$; $P < 0.001$.

Prediction models

Tables 3 and 4 show mixed models using observed or self-reported physical exposure variables to predict mean, 90th percentile, and cumulative EMG. Figure 1 demonstrates the modeling process using the observation-model predicted mean EMG as a function of mean measured EMG. Bivariate results were extensive and are not shown, but tables are available on request to the corresponding author. At the bivariate level, a large number of observed postural variables were significant predictors of EMG, but only a portion of the postural variables that were significant in bivariate analysis were significant in the final models. Fewer self-reported than observed exposure variables were significant in bivariate analysis, though a number of self-reported postural and manual material handling variables were offered to the mixed models.

DISCUSSION

Performance of EMG prediction models

In the current study, models based on self-reported variables predicted between 21 and 36% of the variability in EMG activity, whereas models based on observed variables predicted between 30.7 and 47.2%. Prior studies of positive relationships between back disorders and self-reported and observed exposures indicate face validity for these methods (Kumar, 1990; Knibbe and Friele, 1996; Macfarlane *et al.*, 1997; Myers *et al.*, 1999). However, it is fair to question whether explaining 20–50% of the variability in EMG activity is adequate for epidemiological study. In occupational hygiene, ‘determinants of exposure’ studies of airborne chemicals often explain 30–60% of the variance in directly measured exposure and have been used successfully for exposure assessment in epidemiological studies (Burstyn and Teschke, 1999). EMG differs from airborne chemical exposures in that it is dependent on multiple external factors (such as manual materials handling, or MMH, and posture) and internal factors (muscle recruitment patterns, fitness and muscle fatigue). Although Chen *et al.* (2004) do not state the percentage of whole-body vibration variability explained by their taxi-driving model, they cite average relative prediction errors of 11% and acknowledge that a substantial portion of the variability (48%) is explained by the random variable ‘subject’; the percentage explained by observed and self-reported variables could not be much >50%. The higher relative unexplained variance in the current study may be due to the general nature of the observed determinants that were intended to span multiple industries, job titles, and tasks as compared to taxi-driver-specific determinants such as vehicle, seat, tire, and fare characteristics. For a measure of physical exposure as complex and multifactorial as EMG activity, it is not surprising that the proportion of variability explained be lower than typical.

The estimates of EMG activity given by the models presented do not (and are not expected to) deliver a perfect estimate of an individual's measured EMG exposure. Rather, their value is for epidemiological study of many workers. This has been acknowledged in prior comparisons of direct measurements versus observation and self-report methods. A study comparing spinal compression estimates from checklists, video digitization, work sampling, and self-report in a study of low back pain found that all methods gave significant odds ratios, but questionnaires were deemed more appropriate for large-scale studies and biomechanical modeling for individual assessments (Neumann *et al.*, 1999).

This introduces a price-precision trade-off inherent in selecting an exposure assessment method. In this study, the models based on self-reports explained a lower percentage of variability and have been previously shown to be poorer predictors of physical exposure than models based on observed variables (Barriera-Viruet *et al.*, 2006). However, self-report requires far less time and expense, making it an attractive option for epidemiological studies when large samples are required (Trask *et al.*, 2007). The trade-off between exposure data quality and quantity has been widely acknowledged (Winkel and Mathiassen, 1994; Burdorf *et al.*, 1997; van der Beek and Frings-Dresen, 1998) and has led to the suggestion of cost-effective 'dual-method' or 'validation' exposure assessment strategies where an affordable exposure assessment method is used for the whole sample and concurrent measurements with a more costly method are made on a subsample to allow for modeling (Duan and Mage, 1997).

For all models, the majority of significant relationships with EMG metrics were with posture or manual materials handling variables, both of which require low back muscle activity. These exposures are important to back injury as direct and indirect risk factors; sustained and non-neutral postures and manual materials handling are related to low back disorders and pain reporting (Burdorf *et al.*, 1991; Keyserling, 2000; Kerr *et al.*, 2001; da Costa and Vieira, 2009).

Posture

The total time observed sitting was associated with decreased cumulative EMG. Sitting requires very little back muscle activity and workers are unlikely to be performing manual materials handling while seated. Four of five observed trunk flexion variables were significant in bivariate analyses; the 20–45° flexion category had the largest effect estimates. Interestingly, the trunk flexion categories of 20–45° and >60° were significant predictors of mean and 90th percentile activity, but cumulative activity was predicted by intermediate categories of 10–20° and 45–60°. Although trunk flexion clearly increases predicted EMG activity, the ranges of flexion that are included differed between metrics, most likely because of correlation between categories of posture.

Self-reported 'sitting' was associated with decreased mean and 90th percentile EMG, while self-reported 'sitting while twisting' was associated with decreased predicted mean, cumulative, and 90th percentile EMG. 'Walking while twisting' may be a surrogate for carrying or loading tasks, and 'sitting while twisting' may be a surrogate for extended seated tasks but the inclusion of these variables rather than other more general variables in the final self-report model may be a consequence of poor precision of the self-reports, or chance, since these positions represent a small proportion of working time. Self-reported trunk postures did not predict EMG metrics in the final models; only '10–20°' and 'extended trunk' were significant in bivariate analyses and thus offered to the model.

Manual materials handling

Manual materials handling has a clear and documented relationship to muscle force and spinal loads (Waters *et al.*, 1993; da Costa and Vieira, 2009). As was expected, observed and self-reported time spent handling loads were included in several models. Overall, 3.7% of all observed time was spent handling loads in the 4.5–10 kg range and 2.1% for the next most common range, 10–20 kg. Although this is not a large proportion of observed time, these variables were fairly evenly distributed among the workers, so that nearly all individuals handled such weights for some time during a shift. All three EMG metrics were also associated with observed and/or self-reported handling of loads at extended distance from the body. The horizontal distance of loads in the hands from the body increases the moment arm at the lumbar joint and requires more torque to be generated by the back extensor muscles (Waters *et al.*, 1993).

Industry

'Industry' explained a substantial amount of variance in mean and 90th percentile EMG in the self-reported models; without the 'industry' variable, the self-report-based 90th percentile model explained 33% and the mean model explained 29% of the variance (compared to 36% with industry included). EMG activity was significantly higher in construction and forestry (jobs with frequent bending and MMH) than in transportation (jobs with sedentary vehicle operation). Several self-reported posture and manual materials handling variables were significant predictors in bivariate models and were offered to the multivariate models. That they were not included suggests that the 'industry' variable is better at accounting for the differences between individuals than self-reported manual materials handling or trunk posture. Industry is one of the fastest, easiest, and most reliable pieces of information to acquire; it can be obtained from self-report or workers' compensation classification registries. However, the inclusion of 'industry' in the model limits the applicability of these models to other heavy industries, such as mining or oil and gas that might have comparable postural or manual materials handing exposures. The small proportion of variance explained by the self-report models and the inclusion of unexpected or under-represented activities (such as walking while twisting) may limit the utility of the self-report model in any industry.

Measurement issues and limitations

EMG measurement has some limitations. Worksite conditions like heat, cold, wet, dust, and vibration, as well as pressure or contact from tight spaces, seat backs, or safety equipment, sweating caused by extended exertion, or tugging on the electrode cables (Trask *et al.*, 2007). Although these factors can introduce noise and can result in misclassification of exposure, care was taken to remove data with identifiable artifacts. The amount removed ranged from 1 to 5% of the shift for roughly 30% of measured work shifts. It is hard to predict how missing data affected the subsequent models. If EMG data collection was interrupted only when work became very strenuous due to sweating or increased tugging on cables during dynamic movements, then the net effect would be EMG measures underestimating true working exposures.

Flexion-relaxation response may also have an impact on the EMG measurements upon which the models are based. Deep and sustained forward flexion has been shown to inhibit back extensor muscle activity (Solomonow *et al.*, 2003). In lab studies, this effect has been shown to decrease spinal loads estimated by EMG (Mientjes *et al.*, 1999). In cases where forward flexion is frequent or sustained, EMG could be indicating 'low exposure' even when observed, self-reported, and biomechanically modeled measures of exposure would estimate 'high exposure'. If this was the case, the mismatch would decrease the ability of observed- and self-report-based models to estimate the true exposures. This does not appear to be the case in the current study; observed 'flexion of $>60°$' accounted for $\sim$5% of the total observed time and was positively related to both mean and 90th percentile EMG activity.

The quality of observation and self-report may also influence the models. Observation-based estimates, although recorded by trained observers, are still subject to some level of interpretation and cannot be considered completely objective. Difficulties were encountered when trying to observe workers that were moving throughout the worksite (e.g. maintenance personnel or forklift drivers), resulting in some missing or incomplete observations. However, a validation study of the observation technique used here showed it compared well to direct measures of trunk posture using an inclinometer (Village *et al.*, 2009).

Care was taken during the interview to provide diagrams of the tasks, postures, and loads in question to establish a level of trust that would facilitate candid responses and not to influence worker responses. Nonetheless, workers expressed difficulty in reporting cumulative exposures such as the 'total amount of time spent walking during the day' or the 'total amount of time spent lifting, lowering, pushing, or pulling'. This difficulty is reflected in self-reported durations summing to over 100% of working time. This identifiable misclassification at long durations suggests that there is also unidentifiable misclassification at shorter durations. In a recent review comparing self-report to observation and direct measurement (Barriera-Viruet *et al.*, 2006), self-report was seen to be feasible, economical, and easy to analyze, but it was determined to have 'questionable validity' for work-related physical variables due to its subjective nature. Previous studies have that shown self-reports are less precise than observation and direct measure (Neumann *et al.*, 1999) and that workers tend to over-report physical exposures (Spielholz *et al.*, 2001) or under-report breaks (Unge *et al.*, 2005); these differences are more pronounced when workers have pain (Hansson *et al.*, 2001; Balogh *et al.*, 2004).

Limitations in generalizability

This study included a variety of industries, worksites, jobs, and tasks, including non-cyclical, dynamic, and physically heavy work. Nonetheless, the sample was not intended to be representative of the included jobs or worksites and should be considered an introduction to working exposures in heavy industry. Although the job titles and tasks included in the study are likely to have overlap with those in other industries and may help inform future studies of industries such as mining or agriculture, extrapolating the results to other industries should be done with caution. This is particularly true for the self-report-based models that include industry as a predictor of EMG.

Variables that were significant within their conceptual groups were retained in the final models to maximize their potential success when applied to a different sample. These models were also analyzed with these non-significant variables removed. The models predicted, on average, 5% (range <1–10%) less of the variability in EMG exposure without these variables. Nonetheless, these variables were retained to allow posture and manual materials handling variables considered most directly related to exposure to remain in the models. As with all regression models developed on a certain dataset, the models presented here capitalize on chance. That is, the performance and specific slopes and intercepts from regression analysis would not be exactly the same in another dataset. Certainly one would not expect these models to perform as well on another dataset, even in another sample from the same industries, companies, job titles, and workers as included in this study. The proportions of variance explained by the models can therefore be considered an upper limit or 'best case' for model performance. It would be possible to develop models based on half the data available in the current dataset, and then test the model on the remaining half of the data. However, this would have been at the expense of model quality and so was not undertaken. The models presented here should be pilot tested in the work settings of interest before a large-scale epidemiological study is undertaken.

Conclusion

Predictive models of low back muscle activity based on observed exposures provide low-cost alternatives to direct measures for epidemiological studies. Observed variables predicted 47 and 43% of variability in mean and 90th percentile EMG activity, respectively, but self-report models predicted only 21–36% of the variability in EMG activity using variables such as 'industry' and 'sitting while twisting'. The self-report methodology used in this study had one-tenth the cost of the observation method (Trask *et al.*, 2007) and would allow for a larger sample size within a given budget. Unfortunately, self-report was a poorer predictor and less precise method that would therefore require a larger number of subjects to have the power to identify relationships (Siemiatycki *et al.*, 1989). Differences in predictive power between the models should be evaluated within the context of a proposed study's goals and hypotheses. The results of this study indicate that observation-based estimates of 90th percentile or mean EMG could be expected to perform well, but self-report-based models, particularly for cumulative EMG, should be treated with more caution.

The ability to identify exposure–response relationships is dependent on the quality of the exposure assessment. There are undoubtedly trade-offs between the precision of exposure measurements, their cost, and the number of measurements that can be made. Future research should quantify the trade-off between exposure assessment cost and precision.

SUPPLEMENTARY MATERIAL

Supplementary Tables 1 and 2 can be found at http://annhyg.oxfordjournals.org/

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REFERENCES

Armstrong B. (1995) Study design for exposure assessment in epidemiological studies. Sci Total Environ; 168: 187–94.

Balogh I, Orbaek P, Ohlsson K *et al*. (2004) Self-assessed and directly measured occupational physical activities—influence of musculoskeletal complaints, age and gender. Appl Ergon; 35: 49–56.

Barriera-Viruet H, Sobeih TM, Daraiseh N *et al*. (2006) Questionnaires vs observational and direct measurements: a systematic review. Theor Issues Ergon Sci; 7: 261–84.

Brinkmann P, Biggemann M, Hilweg D. (1988) Fatigue fracture of human lumbar vertebrae. Clin Biomech; 3 (Suppl 1): 1–23.

Burdorf A. (1992) Exposure assessment of risk factors for disorders of the back in occupational epidemiology. Scand J Work Environ Health; 18: 1–9.

Burdorf A. (2005) Identification of determinants of exposure: consequences for measurement and control strategies. Occup Environ Med; 62: 344–50.

Burdorf A, Govaert G, Elders L. (1991) Postural load and back pain of workers in the manufacturing of prefabricated concrete elements. Ergonomics; 34: 909–18.

Burdorf A, Rossignol M, Fathallah FA *et al*. (1997) Challenges in assessing risk factors in epidemiologic studies on back disorders. Am J Ind Med; 32: 142–52.

Burdorf A, van der Beek AJ. (1999) In musculoskeletal epidemiology are we asking the unanswerable in questionnaires on physical load? Scand J Work Environ Health; 25: 81–3.

Burstyn I, Teschke K. (1999) Studying the determinants of exposure: a review of methods. Am Ind Hyg Assoc J; 60: 57–72.

Burstyn I, Teschke K, Kennedy SM. (1997) Exposure levels and determinants of inhalable dust exposure in bakeries. Ann Occup Hyg; 41: 609–24.

Chen JC, Chang WR, Shih TS *et al*. (2004) Using exposure prediction rules for exposure assessment: an example on whole-body vibration in taxi drivers. Epidemiology; 15: 293–9.

Cooper G, Ghassemieh E. (2007) Risk assessment of patient handling with ambulance stretcher systems (ramp/(winch), easi-loader, tail-lift) using biomechanical failure criteria. Med Eng Phys; 29: 775–87.

da Costa BR, Vieira ER. (2009) Risk factors for work-related musculoskeletal disorders: a systematic review of recent longitudinal studies. Am J Ind Med; 14: 14.

David GC. (2005) Ergonomic methods for assessing exposure to risk factors for work-related musculoskeletal disorders. Occup Med (Lond); 55: 190–9.

Drake JD, Callaghan JP. (2009) Intervertebral neural foramina deformation due to two types of repetitive combined loading. Clin Biomech (Bristol, Avon); 24: 1–6.

Duan N, Mage DT. (1997) Combination of direct and indirect approaches for exposure assessment. J Expo Anal Environ Epidemiol; 7: 439–70.

Ferguson SA, Gaudes-MacLaren LL, Marras WS *et al*. (2002) Spinal loading when lifting from industrial storage bins. Ergonomics; 45: 399–414.

Hansson GA, Balogh I, Bystrom JU *et al*. (2001) Questionnaire versus direct technical measurements in assessing postures and movements of the head, upper back, arms and hands. Scand J Work Environ Health; 27: 30–40.

Jones T, Kumar S. (2007) Assessment of physical demands and comparison of multiple exposure definitions in a repetitive sawmill job: board edger operator. Ergonomics; 50: 676–93.

Karlqvist LK, Hagberg M, Koster M *et al*. (1996) Musculoskeletal symptoms among computer-assisted design (CAD) operators and evaluation of a self-assessment questionnaire. Int J Occup Environ Health; 2: 185–94.

Keir PJ, MacDonell CW. (2004) Muscle activity during patient transfers: a preliminary study on the influence of lift assists and experience. Ergonomics; 47: 296–306.

Kerr MS, Frank JW, Shannon HS *et al*. (2001) Biomechanical and psychosocial risk factors for low back pain at work. Am J Public Health; 91: 1069–75.

Keyserling WM. (2000) Workplace risk factors and occupational musculoskeletal disorders, Part 1: a review of biomechanical and psychophysical research on risk factors associated with low-back pain. AIHAJ; 61: 39–50.

Knibbe JJ, Friele RD. (1996) Prevalence of back pain and characteristics of the physical workload of community nurses. Ergonomics; 39: 186–98.

Kumar S. (1990) Cumulative load as a risk factor for back pain. Spine; 15: 1311–6.

Lavender SA, Conrad KM, Reichelt PA *et al*. (2007) Designing ergonomic interventions for emergency medical services workers—part III: bed to stairchair transfers. Appl Ergon; 38: 581–9.

Macfarlane GJ, Thomas E, Papageorgiou AC *et al*. (1997) Employment and physical work activities as predictors of future low back pain. Spine; 22: 1143–9.

Mathiassen SE, Burdorf A, van der Beek AJ. (2002) Statistical power and measurement allocation in ergonomic intervention studies assessing upper trapezius EMG amplitude. A case study of assembly work. J Electromyogr Kinesiol; 12: 45–57.

Mathiassen SE, Nordander C, Svendsen SW *et al*. (2005) Task-based estimation of mechanical job exposure in occupational groups. Scand J Work Environ Health; 31: 138–51.

Mientjes MI, Norman RW, Wells RP *et al*. (1999) Assessment of an EMG-based method for continuous estimates of low back compression during asymmetrical occupational tasks. Ergonomics; 42: 868–79.

Moller T, Mathiassen SE, Franzon H *et al*. (2004) Job enlargement and mechanical exposure variability in cyclic assembly work. Ergonomics; 47: 19–40.

Moore JS, Garg A. (1995) The Strain Index: a proposed method to analyze jobs for risk of distal upper extremity disorders. Am Ind Hyg Assoc J; 56: 443–58.

Myers AH, Baker SP, Li G *et al*. (1999) Back injury in municipal workers: a case-control study. Am J Public Health; 89: 1036–41.

Neumann WP, Wells RP, Norman RW *et al*. (1999) Comparison of four peak spinal loading exposure measurement methods and their association with low-back pain. Scand J Work Environ Health; 25: 404–9.

Ngatia M, Gonzalez D, San Julian S *et al*. (2009) Equivalence versus classical statistical tests in water quality assessments. J Environ Monit; 12: 172–7.

Nieuwenhuijsen MJ, Gordon S, Harris JM *et al*. (1995) Variation in rat urinary aeroallergen levels explained by differences in site, task and exposure group. Ann Occup Hyg; 39: 819–25.

Nordander C, Balogh I, Mathiassen SE *et al*. (2004) Precision of measurements of physical workload during standardised manual handling. Part I: surface electromyography of m. trapezius, m. infraspinatus and the forearm extensors. J Electromyogr Kinesiol; 14: 443–54.

Norman R, Wells R, Neumann P *et al*. (1998) A comparison of peak vs cumulative physical work exposure risk factors for the reporting of low back pain in the automotive industry. Clin Biomech; 13: 561–73.

Preller L, Kromhout H, Heederik D *et al*. (1995) Modeling long-term average exposure in occupational exposure-response analysis. Scand J Work Environ Health; 21: 504–12.

Rubin DI. (2007) Epidemiology and risk factors for spine pain. Neurol Clin; 25: 353–71.

Shelerud RA. (2006) Epidemiology of occupational low back pain. Clin Occup Environ Med; 5: 501–28v.

Siemiatycki J, Dewar R, Richardson L. (1989) Costs and statistical power associated with five methods of collecting occupation exposure information for population-based case-control studies. Am J Epidemiol; 130: 1236–46.

Sobti A, Cooper C, Inskip H *et al*. (1997) Occupational physical activity and long-term risk of musculoskeletal symptoms: a national survey of post office pensioners. Am J Ind Med; 32: 76–83.

Solomonow M, Baratta RV, Banks A *et al*. (2003) Flexion-relaxation response to static lumbar flexion in males and females. Clin Biomech (Bristol, Avon); 18: 273–9.

Spielholz P, Silverstein B, Morgan M *et al*. (2001) Comparison of self-report, video observation and direct measurement methods for upper extremity musculoskeletal disorder physical risk factors. Ergonomics; 44: 588–613.

Stock SR, Fernandes R, Delisle A *et al*. (2005) Reproducibility and validity of workers' self-reports of physical work demands. Scand J Work Environ Health; 31: 409–37.

Svendsen SW, Mathiassen SE, Bonde JP. (2005) Task based exposure assessment in ergonomic epidemiology: a study of upper arm elevation in the jobs of machinists, car mechanics, and house painters. Occup Environ Med; 62: 18–27.

Teschke K, Trask C, Village J *et al*. (2009) Measuring posture for epidemiology: comparing inclinometry, observations, and self-reports. Ergonomics; 52: 1067–78.

Trask C, Teschke K, Village J *et al*. (2007) Measuring low back injury risk factors in challenging work environments: an evaluation of cost and feasibility. Am J Ind Med; 50: 687–96.

Unge J, Hansson GA, Ohlsson K *et al*. (2005) Validity of self-assessed reports of occurrence and duration of occupational tasks. Ergonomics; 48: 12–24.

van der Beek AJ, Frings-Dresen MH. (1998) Assessment of mechanical exposure in ergonomic epidemiology. Occup Environ Med; 55: 291–9.

Village J, Frazer M, Cohen M *et al*. (2005) Electromyography as a measure of peak and cumulative workload in intermediate care and its relationship to musculoskeletal injury: an exploratory ergonomic study. Appl Ergon; 36: 609–18.

Village J, Trask C, Luong N *et al*. (2009) Development and evaluation of an observational Back-Exposure Sampling Tool (Back-EST) for work-related back injury risk factors. Appl Ergon; 40: 538–44.

Waters TR, Putz-Anderson V, Garg A *et al*. (1993) Revised NIOSH equation for the design and evaluation of manual lifting tasks. Ergonomics; 36: 749–76.

Wells R, Norman R, Neumann P *et al*. (1997) Assessment of physical work load in epidemiologic studies: common measurement metrics for exposure assessment. Ergonomics; 40: 51–61.

Winkel J, Mathiassen SE. (1994) Assessment of physical work load in epidemiologic studies: concepts, issues and operational considerations. Ergonomics; 37: 979–88.

You XI, Senthilselvan A, Cherry NM *et al*. (2007) Determinants of airborne concentrations of volatile organic compounds in rural areas of Western Canada. J Expo Sci Environ Epidemiol; 18: 117–28.